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FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies

Master's Thesis

2024 **Michał Abresz**

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Effects of Investor Confidence on the Returns of Actively Managed ETFs

Master's Thesis

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Study programme: International Economic and Political Studies

Supervisor: Mgr. Anna Kúdeľová

Year of the defence: 2024

Declaration

1. I hereby declare that I have compiled this thesis using the listed literature and resources only.
2. I hereby declare that my thesis has not been used to gain any other academic title.
3. I fully agree to my work being used for study and scientific purposes.

In Prague on

29/07/2024 **Michał Abresz**

References

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Abstract

Are investors rational value maximizers? The recent explosion in the field of behavioral finance led to a significant debate over the nature of portfolio creation and investment strategy of market participants. This thesis evaluates the effect of market confidence indicators on the performance of the largest actively managed ETFs available on the US market. This is done through ARIMA-GARCH modeling employed on the daily market data. Obtained results indicate that there is a significant effect of the investor confidence proxied by the VIX index and bond spreads on the performance of the ETFs evaluated; the effect differs depending on the type of the fund in question. This appears to indicate that indeed investor confidence plays a non-negligible role in the way in which fund managers operate and might significantly affect their performance.

JEL Classification	G02, G11, G12, G23
Keywords	investor confidence, behavioral finance, ETF market, fund performance, fund management
Title	Effects of Investor Confidence on the Returns of Actively Managed ETFs

Abstrakt

Jsou investoři racionální maximalizátoři hodnoty? Nedávný rozmach v oblasti behaviorálních financí vede k debatě o způsobu tvorby portfolia a investiční strategie účastníků trhu. Tato práce hodnotí vliv indikátorů tržní důvěry na výkonnost největších aktivně řízených ETF dostupných na americkém trhu. To je provedeno pomocí ARIMA-GARCH modelu aplikovaného na denní tržní data. Výsledky naznačují, že existuje významný vliv důvěry investorů, approximovaný indexem VIX a spreadem dluhopisů, na výkonnost hodnocených ETF; efekt se liší v závislosti na typu zkoumaného fondu. To naznačuje, že důvěra investorů skutečně hraje nezanedbatelnou roli ve způsobu, jakým správci fondů operují, a může významně ovlivnit jejich výkonnost.

Klasifikace JEL	G02, G11, G12, G23
Klíčová slova	investor confidence, behavioral finance, ETF market, fund performance, fund management
Název práce	Vliv důvěry investorů na výnosy aktivně řízených ETF

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Master Thesis Proposal

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Topic characteristics / Research Question(s):

Behavioral finance has become one of the fastest-growing areas of financial research in the last two decades. Incorporating findings from psychology and sociology into market evaluation allowed for the creation of completely new models that describe, as Meir Statman (2008) accurately puts, "normal" investors. Such an approach allows for a much more in-depth evaluation of investor behavior, revealing phenomena that previously have been deemed to be difficult to explain anomalies. However, there has been limited research into the effects of emotions and cognitive biases on fund managers; those negative effects have already been observed and cataloged at the end of the last century (Pompian, 2006). Still, there has been inadequate effort to understand the underlying reasons for the anomalous behavior of fund managers.

The effects of fear on investors have been well documented; Bee and Neubaum (2014) find that fear and fear-related emotions lead to clouded risk perception pushing them into avoidance strategies. Tyszka (1999) points towards similar conclusions; although not focusing strictly on investment decisions, the findings clearly indicate that an individual's disposition is a huge factor when it comes to financial decisions. Bell (1982) coins the term "regret premium", with clear implications that negative previous investments might affect the approach to further investment of an individual.

In light of all of these findings, it becomes reasonable to assume that fund managers are also affected by the plethora of mental constraints; their compensation, reputation and relationships are all related to the performance of the funds that are put in their care. This paper draws inspiration from research conducted by L.A. Smales (2017), but rather than evaluating aggregate stock performance, it focuses on the biggest US-based exchange-traded funds. Additionally, instead of using Granger Causality and OLS, this paper utilizes ARIMA-GARCH estimation. This methodology is incorporated from the Kúdeľa (2021) and applied to ETFs.

If fund managers' decisions are indeed influenced by their bounded rationality it becomes paramount for the research to also focus on how they can shield or adjust their investment strategies in light of such effects. Given the importance of pooled investment-vehicles research should not only focus on the bounded rationality of fund investors, but also, on the bounded rationality of experts in charge of the funds.

Working hypotheses:

1. Hypothesis #1: ETF Performance is affected by investor sentiment
2. Hypothesis #2: Performance of ETFs of a specific characteristic are affected by investor sentiment

Methodology:

The performance of will be evaluated based on the publicly available data provided by the databases of the corresponding investment entities; any supplementary data will be obtained from the Yahoo Finance Database. Based on the nature of the data an appropriate period will be evaluated, due to the evaluation of time-series data where a serious possibility of autocorrelation can be assumed, ARIMA-GARCH modeling will be used. This approach also allows for assessment of the volatility; especially considering potential heteroskedasticity.

Outline:

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4. Hypothesis
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6. Results
7. Commentary
8. Conclusion
9. Limitations
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Introduction

The building blocks of classical economics are based on rational investors and efficient markets. In such environments, the markets are perfect and all but arbitrage-free, as value-maximizing investors base their behavior on reliably accessible information that they can easily interpret. As Miller and Modigliani (1961) state; “rational” investors prefer more wealth to less and are indifferent to the type of compensation they will receive. However, the emergence of behavioral finance which combines research in the area of psychology with the pre-existing economic theory sheds new light on the way in which investors operate within market conditions.

Meir Statman (2008) describes an everyday investor, as “normal” rather than “rational” in Miller and Modigliani’s (1961) sense. Individuals are prone to being influenced by emotions and cognitive biases, with those effects being capable of having a significant impact on the broader economy (Ricciardi & Simon, 2000). Investors are people with their own lives and struggles; the investments they make are crucial to their life situation, so to expect them to not have any emotional attachment to those investments is short-sighted. Miller (1986) himself points out that stocks are for people not just a simple “bundle of returns”, but rather behind each of these is a personal story; a family business, a retirement scheme and a vast number of other possible circumstances.

If that is the case then one ought to consider how can those impulses influence the performance and behavior of actively managed equity funds. It is not unreasonable to assume that market-wide investor confidence might significantly affect the investment decisions of fund managers. This is why this paper examines the question “Effects of Investor Confidence on the Returns of Actively Managed ETFs”. Potential wide-ranging cognitive biases might have serious consequences not only on the individual funds and investors but also, on the economy as a whole.

While the volume of research evaluating the effects of constrained rationality and emotional biases on investors is rapidly growing there appears to be very limited research into the effects of those constrains and biases on investment vehicles themselves. Evaluating the potential consequences for fund managers is crucial in order to better understand the fundamental behavior of different types of investment funds. Current research appears to be mainly “onesided” focusing on how cognitive biases affect fund investors rather than individuals managing those funds or the investment vehicles themselves. Money pooling investment vehicles are a crucial part of the financial system providing diversification and economies of scale to individual investors active within the financial markets so it is crucial that their innerworkings are understood.

Disruptions in the potential performance of the funds can have significant implications for the economy, simple example being the fact that pension schemes are the biggest private equity funders in the US (Wright-Robbie, 1998). If fund performance can depend on cognitive factors it begs to reason that response in their performance to political and societal upheaval is not merely a calculated risk adjustment, but an arbitrary assessment of individuals running such an entity.

As already mentioned this paper focuses on funds, in the case of this paper ten ETFs are evaluated due to vastly limited research that focuses on those particular investment vehicles. Additionally, the easiness of obtaining the data and their inherent high liquidity makes them a compelling research subject. While the literature concerned with behavioral finance currently focuses primarily on market participants that include different types of funds in their portfolio the research into the ways in which these investment vehicles can be affected by behavioral biases is almost nonexistent. As of writing, there appears to be no substantial research looking into the behavioral effects on the ETF market. Given the increasing importance of those instruments, it becomes clear that such evaluation might be of significant contribution to global financial research. This is crucial especially, considering the fact that the ETF market continues to grow in scale and is becoming more utilized by investors across the markets.

1. Literature Review

1.1 Behavioral Finance

Behavioral Finance is a quickly growing area of economics that aims to explain and understand the mental patterns of individual investors (Ricciardi & Simon, 2008). The description presented by Statman (2008) encapsulates the concept of behavioral finance wonderfully; it is a discipline that aims to study everyday "normal" investors who due to their inherent human nature are severely influenced by emotions and cognitive biases. Often even the most experienced investors might not be able to recognize the effects of cognitive biases on their investment decision process (Gambetti & Giusberti, 2012). That is why the ramifications of potential laps in judgment can have wide-ranging effects on investor behavior and the broader economy. If this is the case then the accurate pricing clause of Efficient Market Hypothesis might not be, as "concrete" as many would think. If market participants are not the stalwart rational beings, but rather individuals prone to miscalculations and omissions, then it might be possible for the anomalous mispricing to arise; one which would occur due to the wide ranging miscalculations on the part of investors (Ball, 2009).

Although, the first foundations in the area of behavioral finance were laid over 100 years ago with George Selden's 1912 "Psychology Of The Stock Market", behavioral finance is still a quickly expanding area of research (Hirshleifer, 2015). No longer in its infancy, it incorporates the findings from the fields of Psychology and Sociology, as well as, completely new branches of economics such as neuroeconomics (Loewenstein et al., 2008).

Evaluating market phenomena through behavioral lens is crucial in order to understand the driving forces behind the investment decisions of individual market participants, further improving the perception of market anomalies. This is especially necessary, as the costs of entering into the stock market have been steadily decreasing and the number of equity investors has been on the rise (Barberis & Thaler, 2002). Understanding the constraints of bounded rationality allows for a much deeper understanding of the effects of market forces.

Behavioral finance aims to understand how the plethora of biases and investors' bounded rationality affect their decision-making processes and how those in turn affect the functioning of the financial markets. Many market anomalies have begun to be explained through the lens of behavioral economics; those efforts have not only been purely academic but have also started being incorporated into the decision-making of portfolio managers (Ricciardi & Simon, 2000). Beginning in the 90s' certain fund managers started to advocate for the incorporation of different behavioral "considerations" into the portfolio creation process; still, it was not until the dot-com bubble that true interest began emerging and behavioral economics began being deemed, as something more than, as Statman (2014) puts it, a collection of different tales of investors being swayed towards misfortune by cognitive biases and errors.

If behavioral aspects of emotions and biases are unavoidable then investors basically cannot act according to Miller's and Modigliani's (1961) proposition stating that more is always better and that investors will no matter what focus on maximizing their financial wealth. Due to a plethora of psychological factors, investors will not always be able to act rationally and will be affected by their psychology. However, if they are aware of the effects of those external factors they can develop techniques and measures aimed at counteracting the detrimental effects of their bounded rationality. This is why evaluating the potential effects of market-wide confidence is so crucial.

1.2 Exchange Traded Funds (ETF)

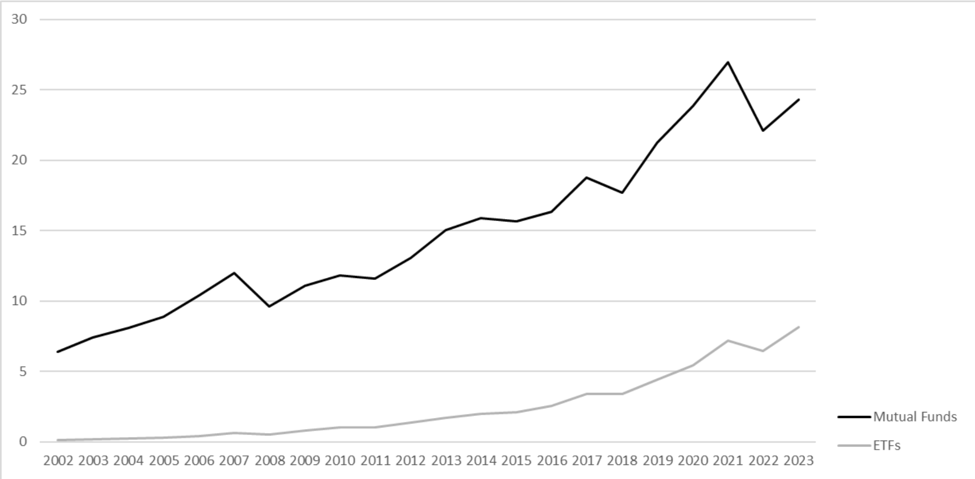
Exchange-Traded Funds (ETFs) are an investment vehicle that closely resembles regular mutual funds. Both act, as a money-pooling entity that invests in certain tradable securities, the nature of which depends on the type of the fund and is specified in the fund's prospectus. The goal of such a solution is to provide portfolio managers with ample capital which they can use to pursue the fund's strategy with the goal of ensuring desirable returns for the fund members. The core characteristic that differentiates ETFs from mutual funds is the fact that the former's shares are traded continuously throughout the day, unlike mutual funds, which only allow investors to buy shares at the end of the day (Ben-David et al., 2017). Equally importantly ETFs do not have minimum entry capital; where mutual funds can require the investor to bear significant entry costs, ETFs require the investor to simply purchase one share plus fees and commissions, significantly reducing the barriers to entry.

ETFs only became a common financial instrument quite recently, becoming a popular investment vehicle alongside the onset of online trading (Pisani, 2023). Still, they revolutionized the asset management world providing investors with low-cost investment vehicles that are highly liquid and prized continuously. Currently, the US ETF industry has assets totaling over 8.12 trillion USD as of 2023, an increase of over 800% since 2011 when the value just crossed the 1 trillion USD mark (ETFGI, 2024). In contrast, the mutual funds have doubled in size in the same period (World Bank, 2024). If the trends continue soon ETFs might begin to rival classical mutual funds in terms of size. Figure 1 showcases the development of ETFs' and mutual funds' assets under management (AUM) between 2002 and 2023.

According to PwC (2024) survey market analysts expect the ETF market to continue to grow at the rate of 17% year-to-year. The share of actively managed ETFs is also growing rapidly making the evaluation of these a crucial factor in understanding future market trends and developments. Those funds are also much more prone to invest in niche markets contributing to the growth in funding in such areas and providing a significant portion of liquidity to growth stocks (JPMorgan Chase & Co., 2024). Ben-David et al. (2017) goes so far as to call ETFs the greatest "game-changer" in the asset management industry of the 21st century; this is argued for due to their combination of low-cost transactions, intraday liquidity and potential for index tracking. A combination that has not been available to investors beforehand. The authors raise the same points as the ones already mentioned in this paper, mainly the limited research into the potential effect of new speculative traders on the quality of the ETFs. Understanding the effects and mechanisms of ETFs is important not only from an academic or professional viewpoint, but also from the regulatory one (Ben-David et al., 2017). This is due to limited knowledge of the systemic risks associated with those investment vehicles, which have so far not been studied, as meticulously, as other financial instruments. The potential volatility, liquidity and information shocks introduced into the market through ETFs might have a substantial detrimental effect on the financial sector and broader economic activity.

Figure 1:

AUMs' development between 2002-2023 for both mutual funds and ETFs



Note. This is the Author's Graph based on ETFGI (2023) values; showcasing development of AUMs' for both regular mutual funds and ETFs. X-axis depicts the year and Y-axis depicts AUM in trillions of USD.
Data Retrieved from:
https://etfgi.com/news/press-releases/2024/01/etfgi-reports-assets-invested-global-etfs-industry-reached-new

By focusing on the ten largest ETFs this paper can utilize a data sample comprised of funds of substantially different investment strategies and risk exposures; additionally, ETFs have significantly more data regarding price and trading volumes, in comparison to significantly less liquid mutual funds. Focusing on ETFs also allows this paper to explore a significantly underdeveloped field, as the already limited research is focused on classic mutual funds.

1.3 Performance of Actively Managed Funds

The phenomenon that actively managed funds tend to underperform compared to their passive counterparts is well known. This has been empirically shown many times (Gruber 1996); Sushko & Turner 2018); as well as, Fama and French (2010), the founders of the famous

Efficient Market Hypothesis. Fama’s (1970) Efficient Market Hypothesis states that market prices reflect all available information with the securities being properly priced.

This would imply that it is not possible for fund managers to identify mispriced securities from which they would be able to profit; making the actively managed funds inferior to their passive counterparts. Nonetheless, there are also findings that point towards the ability of long-term positive alpha to be achieved by certain mutual funds available in the market (Jarrow & Protter, 2011). Findings like that, however, always raise the question of survivorship bias and the correctness of the dataset, as empirical evaluations can often exclude inactive funds. Such issues arise especially in the case of high-yield funds or hedge funds where the proportion of unsuccessful and poorly performing funds is high (Kat & Amin, 2001). Evaluating only well performing funds and excluding the ones that failed to deliver adequate returns obscures the actual machinations at play.

Active investors aim to maximize alpha, defined as the risk-adjusted performance of a portfolio in relation to a benchmark index (Fuller, 2000). They, so to speak, reject the notion of the Efficient Market Hypothesis and believe that they can “beat the market” through expectations of the price changes of traded securities. This is the opposite of passive investing which aims at matching the benchmark return as closely as possible, viewing that due to the Efficient Market Hypothesis long-term positive alpha is unobtainable (Fama and French, 2010).

Still there is a plethora of market anomalies that cast a long shade of doubt over the Efficient Market Hypothesis; overconfidence, herding behavior, lose aversion are just a couple of real life occurrences that ought to not happen to “rational” investors (Hirshleifer, 2015).

Perhaps a behavioral approach might shed more light on the “alpha question”; at the end of the day directors and managers of funds are only human; especially, in the case of actively managed mutual funds decision makers have the freedom to pursue strategies they deem as worthwhile. Such investment decision-making is susceptible to economic irrationality, yet the research into investors’ bounded rationality still finds itself with many questions unanswered (Hirshleifer, 2015).

Herd behavior is a well-documented phenomenon within the industry; it, by no means, is limited to individual investors, but its effects also tend to have a significant impact on the experienced long-term market participants. The impact of herd behavior and cognitive dissonance can clearly be observed when evaluating the dot-com bubble of the early 2000’s.

Traditional investors called fundamental analysts, consistently relied on financial ratios and past performance in order to evaluate companies in which they wished to invest (Ricciardi & Simon, 2000). However, seeing the popularity of the new Internet Companies the same investors started to shift their beliefs and began investing based on market trends, as due to the lack of past financial records of those companies they could not have been evaluated using classical ratio analysis (Ricciardi & Simon, 2000). Investors started to rationalize the change in their investment style by claiming that the world was entering the era of a new economy; this sentiment was widespread across the whole spectrum of market participants (Valliere & Peterson, 2004). Investors started to disregard basic economic principles and started to invest simply based on price momentum (Ricciardi & Simon, 2000). When during the Christmas period the subpar performance of internet providers was revealed the first cracks began to show; selling only accelerated when FED announced interest rate hikes in early 2000 (Goodnight & Green, 2010). At the height of the sell-off, NASDAQ would be decreasing by a percentage point daily (Goodnight & Green, 2010). This combined with the *Barron* releasing estimates that 27% of the companies in the field had negative cashflows and would most likely go bankrupt by the end of the fall led to full-on panic on Wall Street (Kraay & Ventura, 2007). The market value of companies that went through IPOs declined from $1 trillion USD in March to $572 billion USD in December (Goodnight & Green, 2010).

This example clearly exemplifies the effect that investor perception and confidence might have on the stock market, as well as, the broader economy. Understanding the mechanisms behind it might seriously improve the ability to foresee future market bubbles.

1.4 Investor Confidence

Investor confidence can be defined, as the confidence of a market participant in their ability to correctly predict future developments in the market, as well as, measuring the perception of optimism, or lack thereof, in the well-being of the equity market (Meier, 2018).

Following the classical Miller & Modigliani (1961) assumption of rationality confidence should not play any role in the behavior of investors. Risk-aversion of an investor is clearly defined and those investors are able to clearly gauge and evaluate the risk associated with any investment (Miller & Modigliani, 1961). The prior returns and expectations should not play any role in subsequent investment decisions; this, however, appears not to be the case (Brown & Taylor, 2006). Confidence appears to play a significant role in the way in which investors formulate their expectations and predictions (Hirshleifer, 2015).

Multiple ways have been developed in order to measure the level of investor confidence in the stock market; those primarily can be divided into two categories: Investor Surveys and Economic Variable Indexes. The primary concerns when evaluating surveys are the issues typical for the nature of such evaluation; selection bias and response bias can easily creep into the analysis. Similarly, cognitive dissonance is quite common among mutual fund investors, which can distort the reliability of the answers presented by the respondents, especially, considering the fact that such surveys are not immediately answered and released (McGrath, 2017). Quantitative evaluation allows to avoid such issues but can potentially not provide clear answers to questions concerned with the cognitive biases of market participants. This is due to the fact that they “skip” anomalies that can potentially arise from the misalignment of the portfolio and investor expectations. Still, it is a much more efficient measure of potential sentiment biases, such as overconfidence (Berthet, 2021).

Overconfidence is one of the most studied areas of behavioral finance; the plethora of effects it has on investors has been a source of much deliberation (Moore & Healy, 2008); (Pohl, 2022). It refers to the tendency of investors to overestimate their capabilities and skills (Statman, 2008). Market participants will view their judgments to be more accurate than they are in reality leading to undesirable strategies. The effects of overconfidence can be especially prevalent among institutional investors, whose compensation is tied to the returns of the managed portfolio (Hirshleifer, 2015). One of the most crucial aspects of this behavior is excessive trading; significant empirical evidence demonstrates that overconfident investors tend to exhibit much more volatile trading patterns, which in turn negatively affects portfolio returns (Meier, 2018). This behavior often coincides with financial cognitive dissonance and can potentially have “ripple effects”, as overconfidence might strengthen sunk cost fallacy and escalation of commitment (Sleesman et al., 2018).

Statman, Thorley and Vorkink (2006) provide robust empirical evidence of the positive relation between market-wide gains and trading frequency; the findings showcase, a “rollover” in the sentiment, as greater increases in returns result in abnormal trading volume spread in subsequent months. Meier (2018) arrives at the same conclusion specifying that higher security turnover tends to persist for around 2 months and partially reverses in the 3rd month.

2. Data

2.1 Market Confidence Indicators

Market confidence indicators are aimed at quantifying the "outlook" of actors involved in the stock market. Risk perception of investors is one of the crucial determinants of a financial cycle, with high confidence comes investment, whereas, low confidence implies a decreasing risk appetite and spending. For the purposes of this paper two indicators have been selected namely 1) Chicago Board Options Exchange Volatility Index (VIX) and 2) Intercontinental Exchange Inc. Bank of America US High Yield Index Option-Adjusted Spread (Spread). Using a quantitative index with daily values allows for a much more precise evaluation of changes in fund prices compared to results obtained from attitude surveys. This approach avoids having to rely on qualitative surveys, due to the utilization of the actual market data to construct the model. Response surveys tend to be exposed to a significant amount of bias and other issues that can disturb the quality of the gathered data (Bishop, 1990). Additionally, the index captures investors' immediate behavior and risk appetite avoiding data issues that can arise from response or acquiescence bias. Furthermore, using two indicators that are often considered as reliable measures of investor confidence allows for comparison and higher robustness of the results (Ding et al., 2021). Both of these utilize different market data, which allows them to be independent of each other, further strengthening the results:

1) VIX – The Chicago Board Options Exchange (CBOE) has been computing the VIX since 1993 with the aim of quantifying the expectations for the changes in the price of the S&P500 (Fernandes et al., 2014). The data has been obtained from Yahoo Finance Database with the daily closing values for the period of 13/04/2023 – 12/04/2024. Using this approach allows for a quantitative approach which utilizes actual market data; thanks to that VIX is able to provide data in real-time. This is one of the most

recognizable and consistent volatility Indexes published (Corrado & Miller, Jr., 2005). VIX is computed based on the strength of near-term deviations of put and call prices on S&P500 Index options. The formula used to compute VIX is presented below:

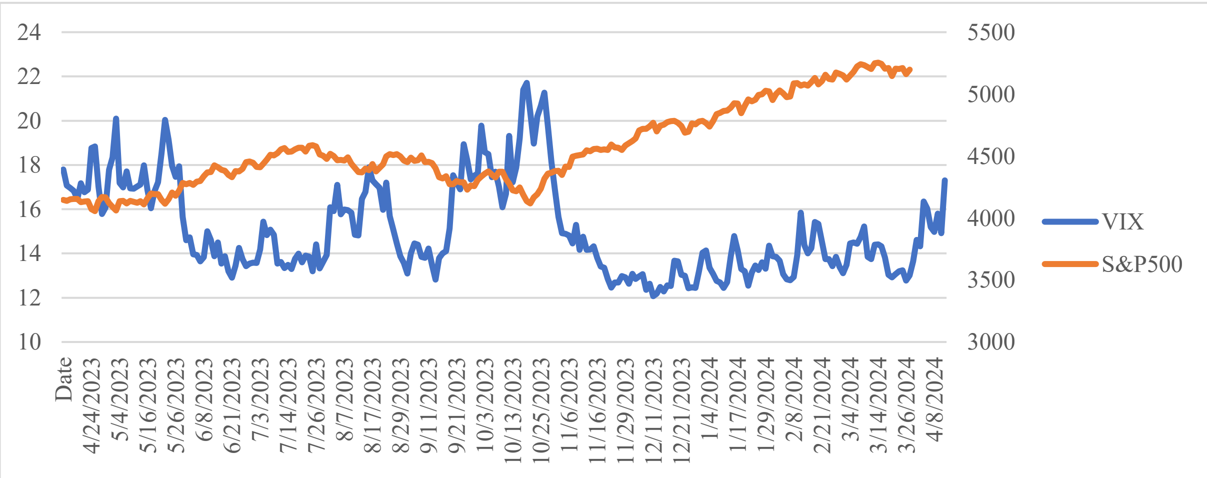
$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left(\frac{F}{K_0} - 1\right)^2 \tag{1}$$

$$VIX = 100\sigma$$

T denotes option's time to expiration in years, F represents option-implied forward price, K_0 first strike price equal or one tick below the forward index level, K_i strike price for out-of-money option number i (call for $K_i > K_0$, put for $K_i < K_0$), R risk-free interest rate to expiration, Q is the mid-point of the bid-ask spread. Higher values of the index indicate higher expected volatility and lower investor confidence, for lower values the relationship is opposite with lower expected volatility and higher confidence.

Figure 2:

Development of Index values for both VIX and S&P500 between April 2023 – April 2024



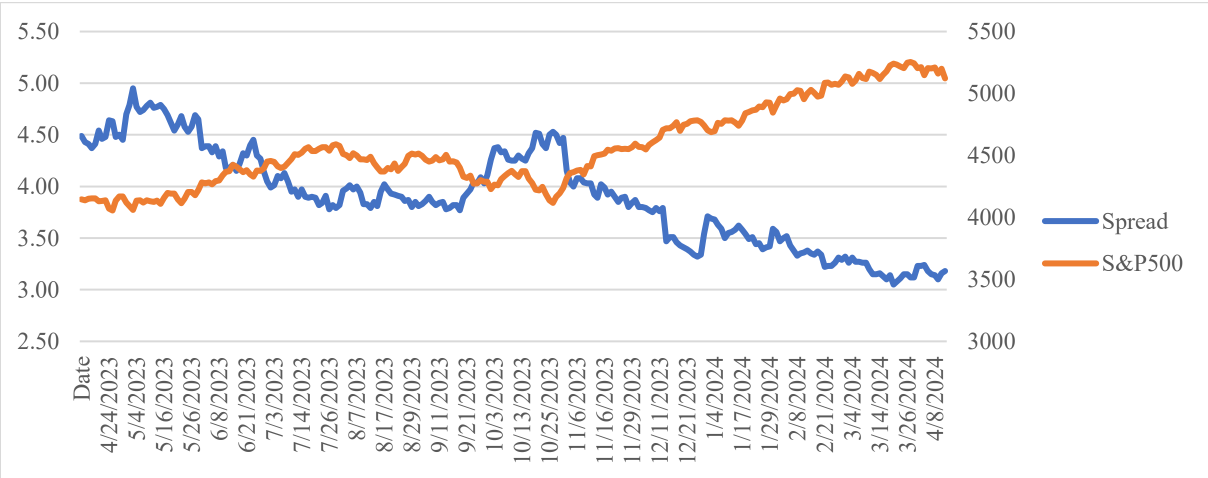
Note. This is a graph showcasing the changes in the values for VIX (blue) and S&P500 index (orange) between 13/04/2023 and 12/04/2024.

Data Retrieved from: https://finance.yahoo.com/quote/%5EVIX/

2) ICE BofA US High Yield Index Option-Adjusted Spread (Spread) – Intercontinental Exchange Inc. (ICE) calculates the spreads between the Option-Adjusted Spread Index of all bonds considered to be below investment grade and a spot US Treasury rate. The index aims to measure the changes in "demand" for riskier instruments in comparison to the near-riskless Treasury spot rates (Nelson & Siegel, 1987). Data used in this paper has been retrieved from the Database of the Federal Reserve Bank of St. Louis for the period 13/04/2023 – 12/04/2024. Usage of spreads allows to indirectly measure the risk-appetite of investors; the spread will be narrow when the investors are willing to "bear" the risk and require a smaller level of "compensation" for that risk. Widening spreads indicate that market participants are flocking to safer investments and demand much greater compensation from the riskier investments.

Figure 3:

Index Values for ICE BofA US High Yield Index Option-Adjusted Spread and S&P500 between April 2023 – April 2024



Note. This is a graph showcasing the changes in the values for Spread (blue) and S&P500 (orange) between 13/04/2023 and 12/04/2024.

Data Retrieved from: https://fred.stlouisfed.org/series/BAMLH0A0HYM2

Observing the movements of both the Spread and VIX against the S&P500 it becomes clear that both variables display similar tendencies; still, VIX displays a much greater degree of volatility compared to the developments for the changes of the Spread. Additionally, from the visual inspection, it does appear that both of these metrics appear to exhibit a certain degree of correlation with the S&P500; further conclusions can be drawn from the descriptive statistics provided for the variables. Vodenska and Chambers (2013) find that VIX and S&P500 display similar Gaussian volatility structures for the subset including the volatilities within two standard deviations around the mean; however, in the cases of tail volatilities in excess of two standard deviations from the mean they begin to diverge significantly. More in-depth evaluation of the correlation between indicators and S&P500 is provided in Chapter 3.7.

Figure 4

Descriptive Statistics of VIX, Spread and S&P500

VIX		*Spread*		*S&P500*	
Mean	15.0450397	Mean	3.89670635	Mean	4566.07492
StError	0.13255294	StError	0.02957085	StError	21.0099593
Median	14.365	Median	3.895	Median	4496.26514
Mode	13.88	Mode	3.9	Mode	4137.64014
StDev	2.10421274	StDev	0.46942266	StDev	333.522764
Variance	4.42771126	Variance	0.22035763	Variance	111237.434
Skewness	0.92880705	Skewness	0.0727361	Skewness	0.57503949
Minimum	12.07	Minimum	3.05	Minimum	4055.98999
Maximum	21.709999	Maximum	4.95	Maximum	5254.3501
Count	252	Count	252	Count	252

Note. This table showcases basic descriptive statistics values for VIX, Spread and S&P500

Given that the values for Skewness for all three variables are within the range of -1 and 1 it is an initial indicator of normality, however, further more comprehensive evaluation will be provided to display normality and stationarity (Hair et al., 2022). The data set has been restricted to values gathered for the dates between 13/04/2023 – 13/04/2024 as bigger samples fail to satisfy the condition of stationarity; only after significant data management can the stationarity be ensured, second-order differencing would allow the funds to be evaluated for the whole duration of their activity. However, such extensive transformations would make it neigh impossible to draw any concrete conclusions from the results obtained; in case of second-order differencing one would evaluate the effects of the “change-in-change” of either price or returns.

The cause for the abovementioned predicament is not that unexpected; most of the funds on the list have been formed between the years 2020-2022 meaning that they have been “thrown” into very volatile and unusual periods of the US economy. The effects of COVID-19, subsequent periods of high-interest rates and War in Ukraine cannot be understated. Evaluation of the funds in the next sub-chapter showcases their characteristics and risks associated with them, it is clear and easily visible that such circumstances "disturb" the data and limiting the evaluation to the period 2023-2024 avoids the issues that arise from the effects of such shifts. Certainly, such action limits the scope of the evaluation, as ideally the consideration of the whole period during which the funds have operated would be ideal. However, such an approach as already mentioned would severely impact the reliability of the results, especially, given the fact that the funds differ in their inception date.

2.2 Funds under consideration

Ten actively managed ETFs have been evaluated; there is little research done on mutual funds, but the volume of research that deals with ETFs is minuscule. The ETFs under consideration are all actively managed; this means that the portfolio they comprise of is evaluated and adjusted on a regular basis aiming to maximize the returns by purchasing and buying securities deemed to be over/undervalued at the moment. Ten biggest US-based ETFs in terms of assets under management, as of March 2024, have been selected. The following section will shortly introduce and describe all the EFTs evaluated.

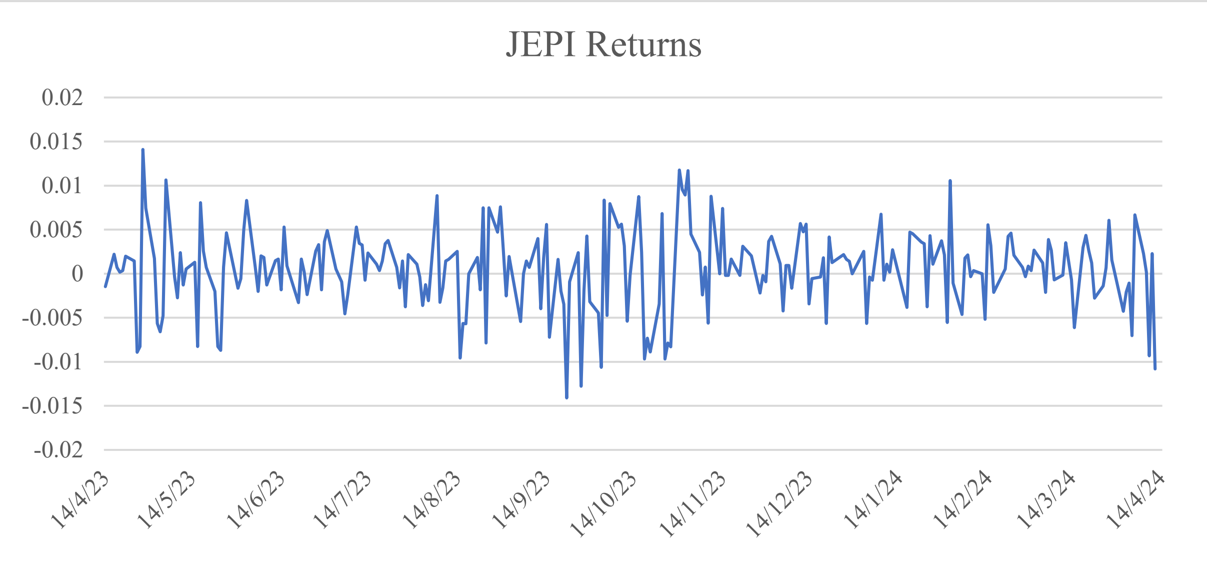
All the data and descriptions of the investment assets presented below have been sourced from official online databases of the corresponding funds and supplemented with data gathered from Yahoo Finance. ETFs are presented in descending order of the volume of assets under management. Additionally, all the graphs showcase the evolution of the returns over the evaluated period.

2.2.1 JPMorgan - Equity Premium Income ETF

The biggest actively managed ETF readily available in the market is JPMorgan's Equity Premium Income ETF with 33.14 billion USD in assets, as of 14/03/2024 (JPMorgan, 2024). Formed on May 20th 2020 the fund maintains an actively managed portfolio of equity securities that primarily consists of stocks and bonds of S&P500 listed companies. The fund maintains a defensive allocation aiming for a low beta while systematically selling one-month call options on the index. The aim of the fund is to replicate the returns associated with the S&P500 benchmark while decreasing the risk exposure associated with the investment into a market portfolio, alongside incremental income. This investment strategy exposes the fund to fundamental risks such as equity risk, market risk and strategy risk. Those can be exemplified due to the heavy concentration of the portfolio that primarily comprises of stocks; nonetheless, there is a clear focus on sector diversification with no industry being allocated more than 15% of the total fund value.

Figure 5:

JEPI Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of JPMorgan Equity Premium Income ETF (JEPI) between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://finance.yahoo.com/quote/JEPI/

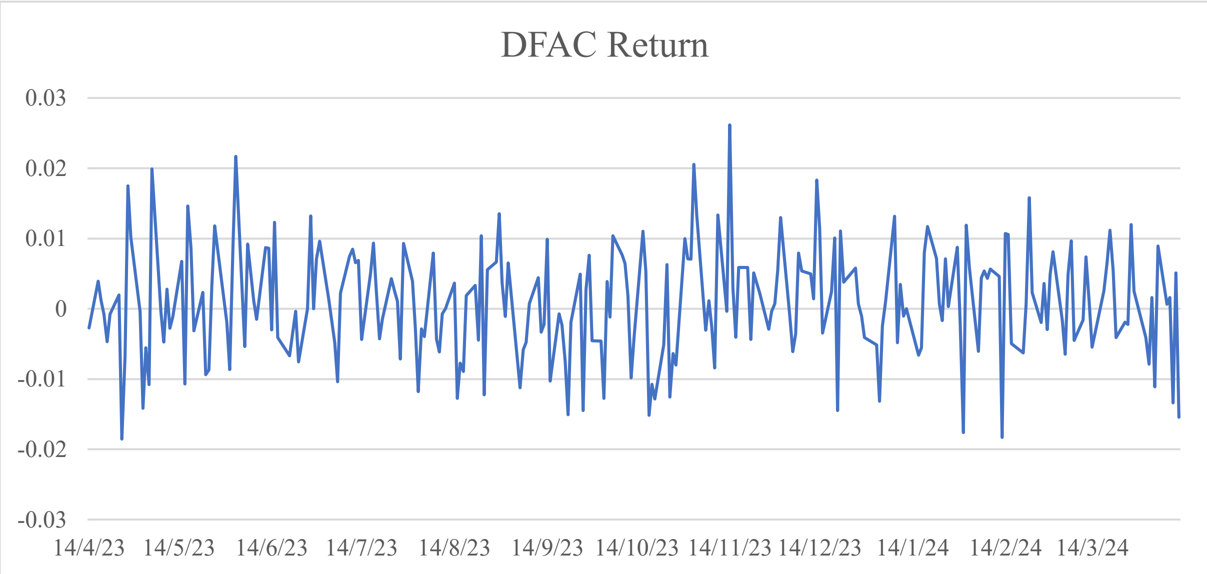
2.2.2 Dimensional - U.S. Core Equity 2 ETF

The second ETF under consideration is Dimensional's U.S. Core Equity 2 ETF with 26.11 billion USD of net assets under management, as of 14/03/2024. The main goal of the fund stated in the prospectus is the maximization of the after-tax value of the shareholder's investment. In order to do so fund's management purchases and sells US-based equity securities, futures contracts and option contracts. The portfolio consists mainly of Russell 3000 securities with the index acting as the fund's performance benchmark; 80% of the fund's holdings are equity securities with the remaining 20% being comprised of futures and option contracts.

The investment strategy exposes the ETF to much greater Tax-Management strategy risk, as the investment objective of the funds is significantly dependent on the changes in federal income taxes on returns. This creates an additional, opportunity for cognitive biases to influence the equity allocation of the fund.

Figure 6:

DFAC Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of Dimensional U.S. Core Equity 2 ETF (DFAC) between 13/04/2023 and 12/04/2024.

Data Retrieved from: https://finance.yahoo.com/quote/DFAC/

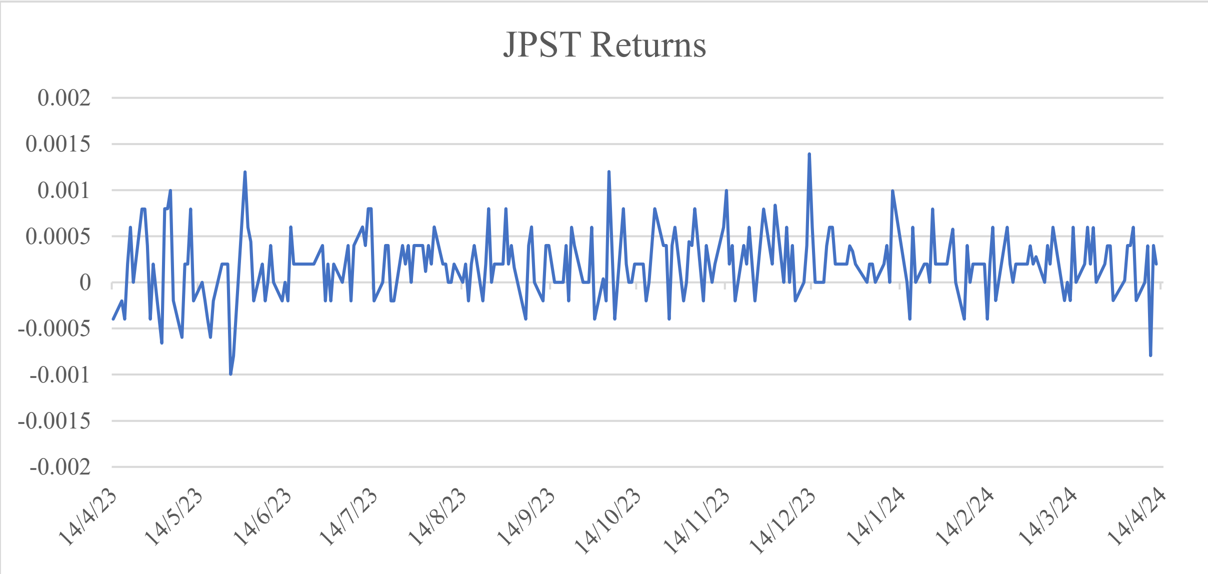
2.2.3 JPMorgan Ultra-Short Income ETF

JPMorgan's Ultra-Short Income ETF invests in short-term investment-grade debt aiming for a low volatility of principal. The funds portfolio comprises of corporate securities, asset-backed securities, mortgage-backed securities and high-quality money market instruments such as commercial papers and certificates of deposits, as well as, treasury securities. The fund concentrates its investments in the banking industry, however, might temporarily diversify out its holdings, as a defensive mechanism. Formed in 2017 the fund provides a low-risk steady yield with a low-expense ratio; with 22.55 billion USD in assets as of 15/03/2024 with a turnover ratio of around 57%.

The high concentration of the fund leaves it exposed to a significant market and sectoral risk, as over half of the total assets of the fund reside in the banking sector. Additionally, due to the nature of the fund, it is faced with interest rate risk, as the frequency and magnitude of the changes in monetary policy might be difficult to predict.

Figure 7:

JPST Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of JPMorgan Ultra-Short Income ETF (JPST) between 13/04/2023 and 12/04/2024.

Data Retrieved from: https://finance.yahoo.com/quote/JPST/

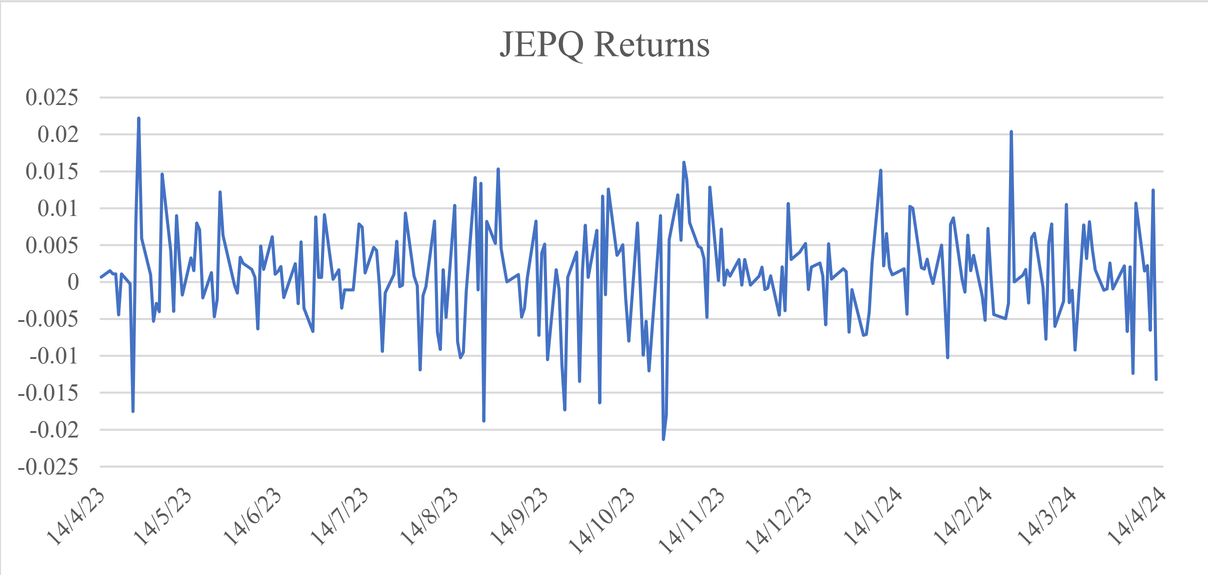
2.2.4 JPMorgan Nasdaq Equity Premium Income ETF

The fund focuses strictly on maximizing current the income of the ETF shareholders, in order to achieve this the fund aims to generate income through a combination of selling options and investing in U.S. large-cap growth stock primarily concentrated within the S&P100 index. Those actions aim to deliver an income stream from the aforementioned option premiums and share dividends.

Founded in May 2020 it manages 10.81 billion USD in assets under management, the fund focuses heavily on the technology sector with limited diversification. This means that the fund is exposed to significant risk connected with the lack of diversification and its performance will be closely tied to the developments within the technology sector in the US.

Figure 8:

JEPQ Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of JPMorgan Nasdaq Equity Premium Income ETF (JEPQ) between 13/04/2023 and 12/04/2024.

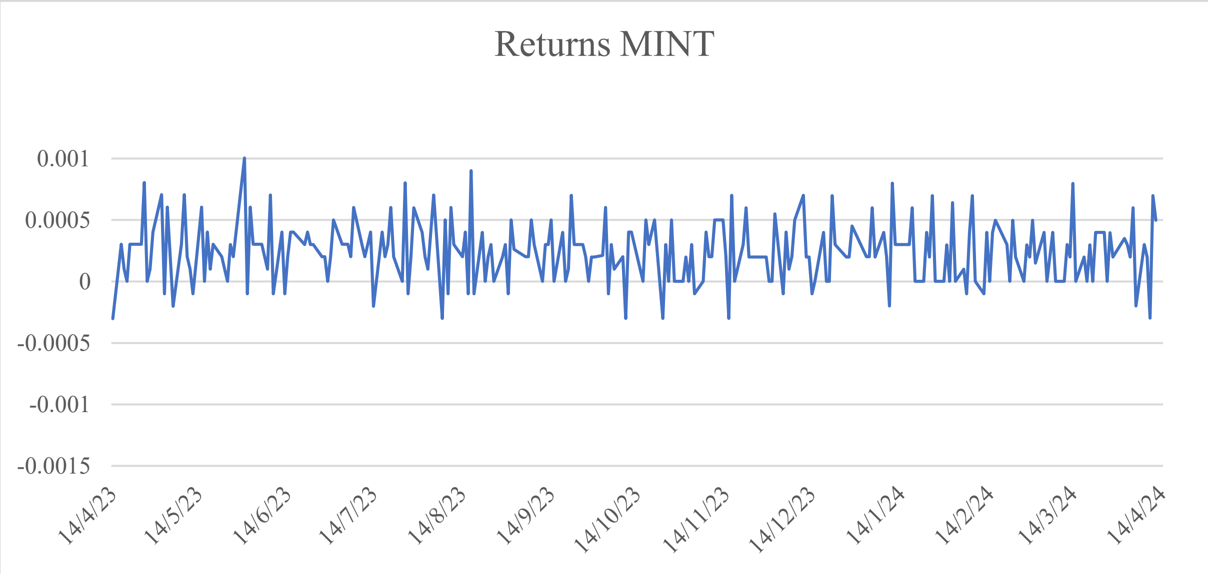
Data Retrieved from: https://finance.yahoo.com/quote/JEPQ/

2.2.5 PIMCO Enhanced Short Maturity Active ETF

PIMCO's Enhanced Short Maturity Active ETF provides investors the ability to buy into short-term corporate debt, that is the debt that matures within one-year. Focusing on investment-grade debt securities with a very significant degree of diversification the fund's exposure to credit and interest rate risk is minor, providing the investors with reliable and safe, albeit low yield. The fund primarily distributes all of its net investment income in the form of monthly dividends. With an inception date of 16/11/2009 and a listing date of April 2014 the fund manages 10.9 billion USD in net assets as of 18/03/2024.

Figure 9:

MINT Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of PIMCO Enhanced Short Maturity Active Exchange-Traded Fund (MINT) between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://finance.yahoo.com/quote/MINT/

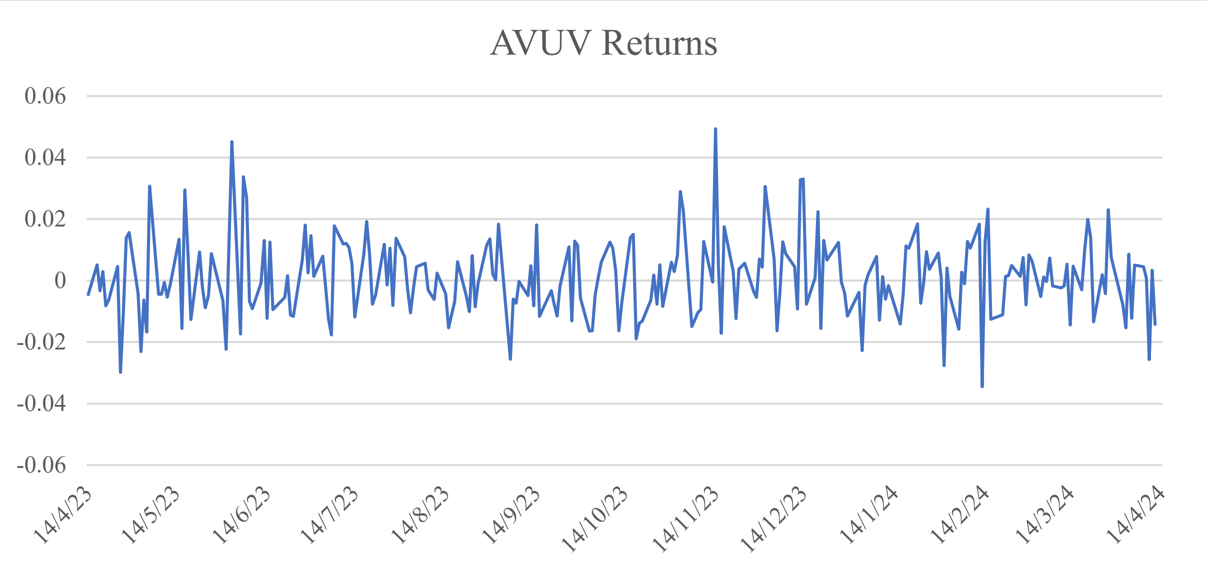
2.2.6 Avantis U.S. Small Cap Value ETF

The fund's primary objective is the maximization of long-term capital appreciation; this is done through investment in a diverse group of US-based small-cap companies. The fund seeks to realize greater expected returns by purchasing securities of enterprises deemed to be undervalued in terms of their market price in relation to their profitability and value growth. Subsequently, the fund's portfolio managers sell securities of companies that are considered no longer desirable in terms of the aforementioned characteristics.

The fund aims for a high degree of diversification and a low turnover ratio, thanks to significant sectoral distribution of investments the fund minimizes the equity securities and industry-specific risk. Nonetheless, due focus on small-cap growth stock the ETF can experience a significant level of small-cap stock risk, smaller companies have less publicly available information and their securities are inherently less liquid and more sensitive to changes in economic conditions.

Figure 10:

AVUV Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of Avantis U.S. Small Cap Value ETF between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://www.avantisinvestors.com/avantis-investments/avantis-us-small-cap-value-etf/

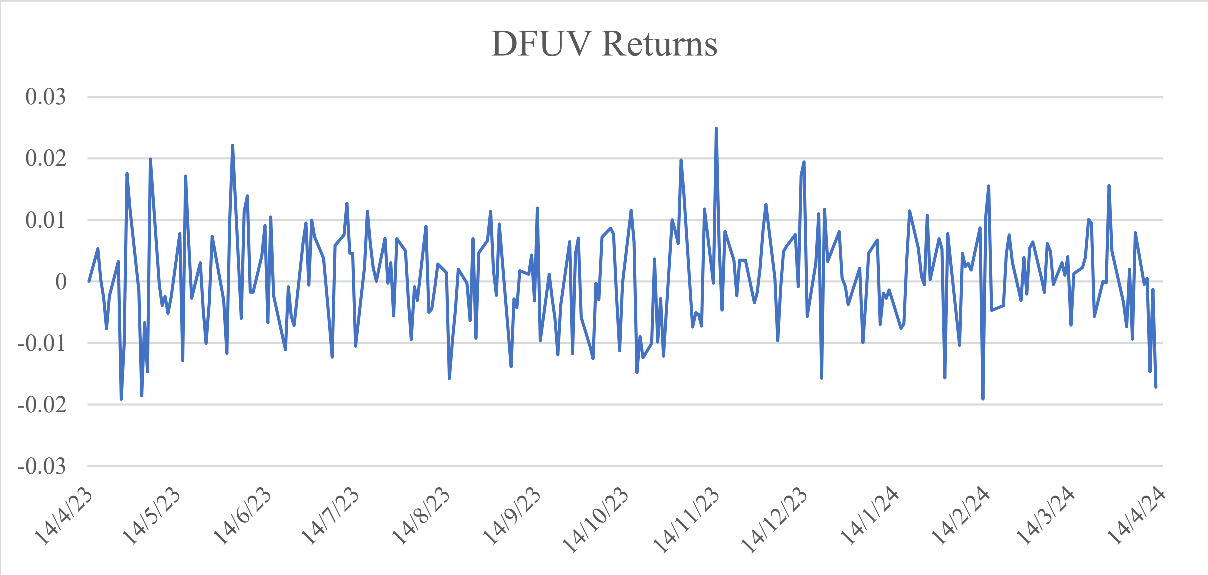
2.2.7 Dimensional US Marketwide Value ETF

Dimensional's US Marketwide Value ETF is primarily concerned with long-term capital appreciation, including after-tax considerations. The fund focuses on US-based value stocks of different industries. The portfolio consists of companies of all market capitalizations that are considered to have a lower relative price to their book value. The holdings are market-cap-weighted with the large-cap stock generally assigned higher weights than their small-cap counterparts.

Founded on 09/05/2022 the fund manages 10.22 billion USD in its assets, as of 18/03/2024. Very significant diversification of the portfolio, which consists of 1344 companies, as of 18/03/2024, significantly reduces the risk to which the fund is exposed, although cannot completely eliminate the market risk.

Figure 11:

DFUV Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of Dimensional US Marketwide Value ETF (DFUV) between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://finance.yahoo.com/quote/DFUV/

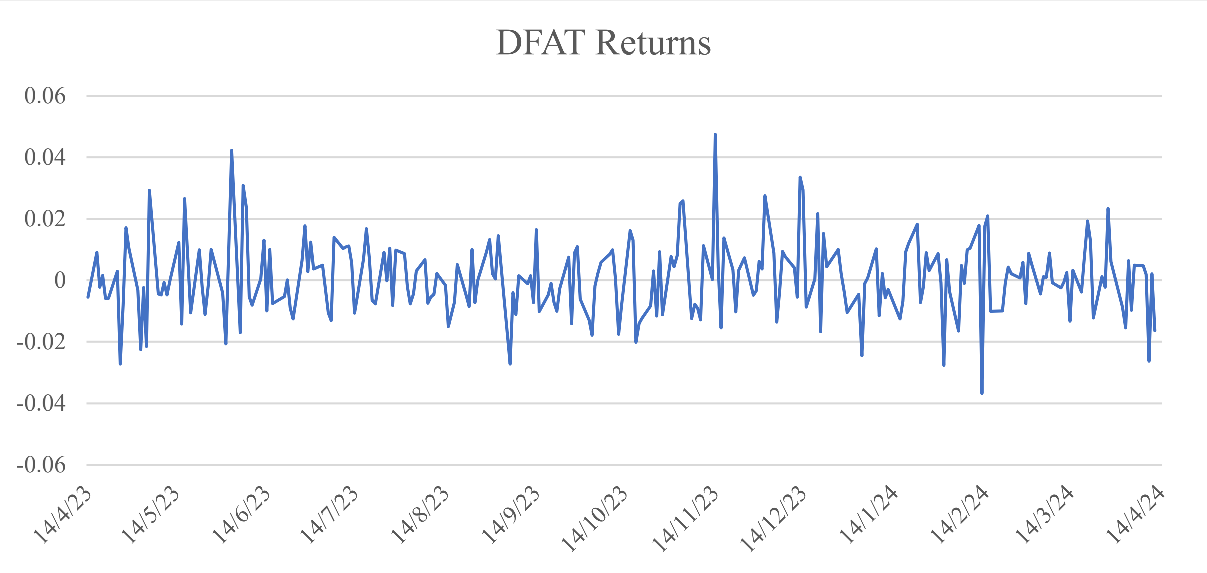
2.2.8 Dimensional U.S. Targeted Value ETF

The 3rd Dimensional fund on the list, US Targeted Value ETF, is similar to the already described US Core Equity 2 EFT, with the focus on long-term after-tax returns through the purchase of US-based equity securities, futures and options contracts. However, U.S. Targeted Value ETF invests only in mid and small-cap companies aiming to acquire stocks of companies with lower relative prices in relation to the enterprise's profitability. The portfolio consists of companies that rank as the lowest 13% of US market capitalization; 80% of the fund holdings consist of equity securities with the remaining 20% consisting of futures and options contracts.

With the fund's listing date of 14/06/2021, DFAT manages 9.5 billion USD in assets, as of 18/03/2024. The fund is heavily diversified, although the focus on small and mid-cap stocks exposes it to liquidity risk and small-cap stock risk. This in combination with inherent market risk can prove significantly detrimental to the potential performance of the fund due to the low trading frequency of smaller enterprises.

Figure 12:

DFAT Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of Dimensional U.S. Targeted Value ETF (DFAT) between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://finance.yahoo.com/quote/DFAT/

2.2.9 Dimensional U.S. Equity ETF

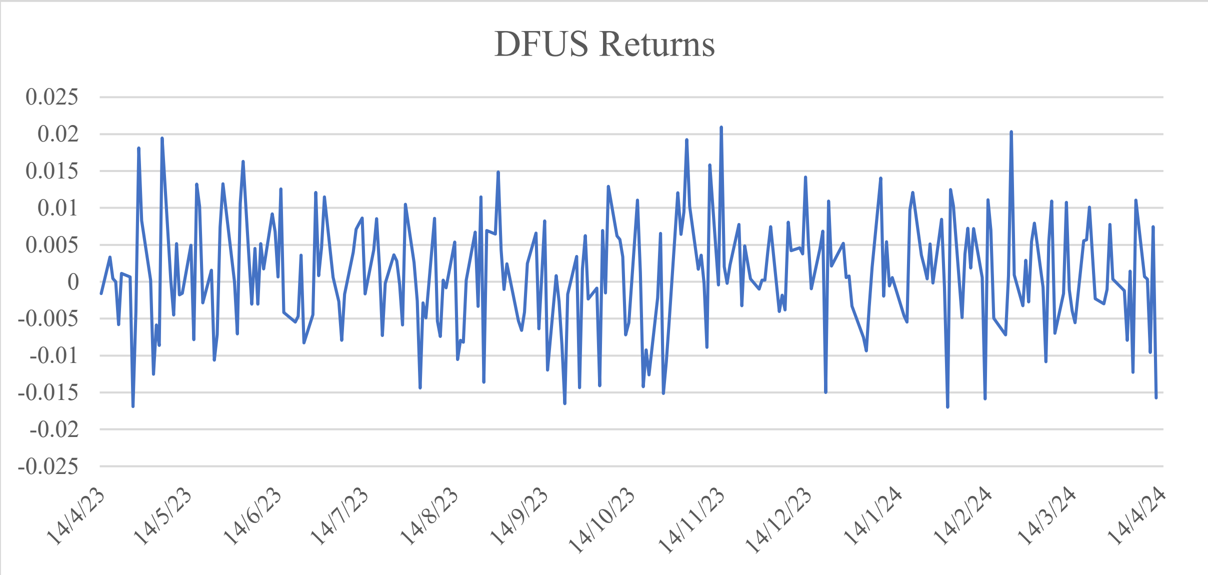
Dimensional's U.S Equity ETF similarly to other Dimensional funds is primarily concerned with minimizing federal income taxes on returns. The fund tends to focus on a blend of value and growth large-cap stocks across a broad range of sectors; the fund is actively managed but has the lowest annual turnover of the ETFs, considered in this paper, of only 2%. Consequently, although it does not aim to replicate the benchmark its performance is very similar to that of Russell's 3000 Index.

The listing date of the fund is the same as other Dimensional ETFs, 14/06/2021, due to Dimensional's policy of periodic mutual fund-to-ETF conversion. As of 18/03/2024, the fund manages assets valued at 8.64 billion USD.

The nature of the fund allows it to minimize its risk exposure, although it certainly does not eliminate the market risk associated with the nature of the portfolio.

Figure 13:

DFUS Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of Dimensional U.S. Equity ETF (DFUS) between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://finance.yahoo.com/quote/DFUS/

2.2.10 ARK Innovation ETF

The last fund under consideration is certainly the most unconventional of the already described ETFs. ARK Innovation seeks long-term capital growth through investment into companies tied to "disruptive innovation"; ARK considers these as technologies that can potentially change the way in which the world operates with a focus on cutting-edge, experimental technology.

Disruptive Innovation Theory originally proposed by Clayton Christensen (1997) is a theory of innovative-driven growth; it describes the way in which after existing established technology becomes entrenched in the market, small companies start to fill the niches in the market with new and innovative solutions that with improvements overtime begin to challenge and perform better than existing solutions. This way the new innovations overtake and make obsolete the old technologies (Christensen et al., 2018).

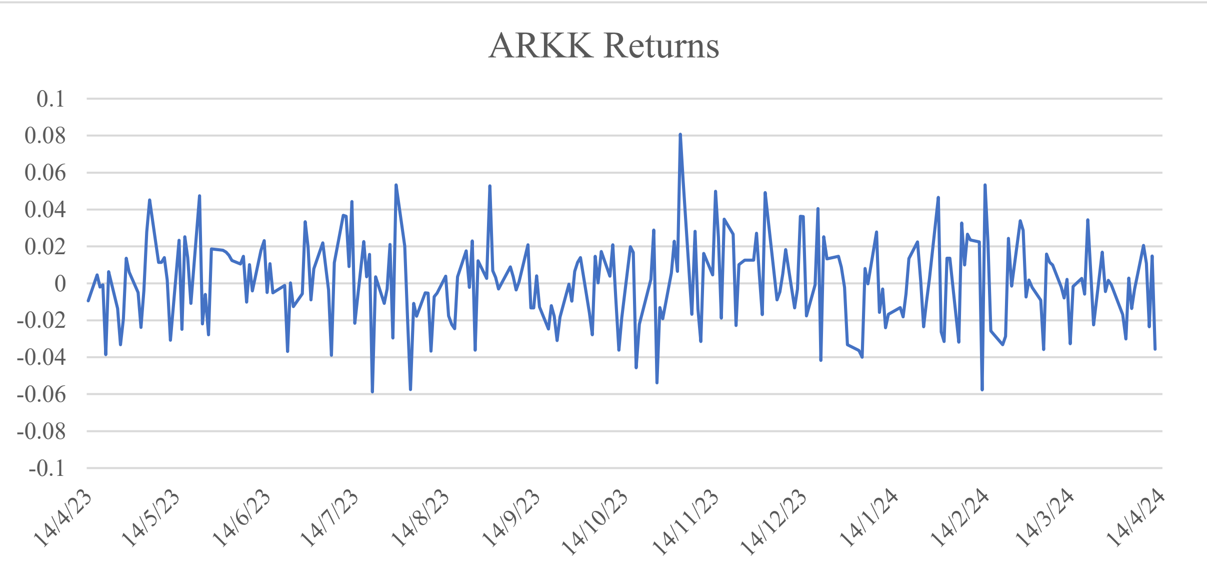
The fund management aims to select investments that have the potential to significantly affect areas such as artificial intelligence, DNA and genome technologies, energy innovation, fin-tech, cloud computing and automation. Unexpectedly, it is also the second oldest ETF from the aforementioned funds proving its longevity. Started on 31/10/2014 its net assets under management, as of 18/03/2024 are valued at 7.5 billion USD.

Clearly, the fund has many characteristics of a venture capital fund, although is not classified, as such, due to the fact that large portions of its portfolio are allocated to already established entities such as TSLA (Tesla Inc.), ROKU (Roku Inc.) and ZM (Zoom Video Communications).

The fund is undoubtedly exposed to a significant degree of risk, ARK Innovation's prospectus lists 24 principal risks to which the ETF has significant exposure. This clearly makes the evaluation of the effects of investor confidence much more puzzling, as there are significantly more potential factors that can influence the performance of this particular fund compared to others listed above.

Figure 14:

ARKK Returns during the period 14/4/23-14/4/24



Note. This graph presents developments in the returns of ARK Innovation ETF (ARKK) between 13/04/2023 and 12/04/2024.
Data Retrieved from: https://finance.yahoo.com/quote/ARKK/

2.3 Commentary on the ETFs under consideration

This short description of the funds showcases that the ten biggest US-based actively managed ETFs vary greatly. The funds differ significantly in their objectives and strategies prioritizing a varied assortment of investment strategies. There are five different investment firms and banks represented ensuring that the results are spread across different business entities minimizing any potential company-specific shocks on the funds.

The funds differ also in portfolio composition and riskiness; additionally, the sample comprises of ETFs with different management approaches and styles. Varied risk exposure ensures that the model's "noise" does not overwhelm the results. This is especially, important, due to a limited number of observations for many of the ETFs due to their relatively recent listing date. Most funds are only 2-3 years old which already does not allow for long-term evaluation and the further reduction in the evaluated period further limits the number of observations.

The ETFs under consideration differ in terms of risk-exposure and turnover; the fact that the ten biggest US-based actively managed ETFs have such varied characteristics allows the evaluation to cover a significant part of the ETF market without focusing on funds of specific characteristics or strategies.

2.4 S&P500

Standard & Poor's 500 (S&P500) index, is one of the most recognizable stock indexes commonly used and reported on; encompassing five hundred biggest US companies in terms of market capitalization. S&P500 covers approximately 80 percent of all public available equity in the US. The index is widely used as a proxy to gauge the US equities market, with its diversity and coverage it is often used to simulate a market portfolio.

The values of the index have been obtained from MarketWatch's historical database and are used in the model to evaluate the effects the market shifts in the US have on the evaluated ETFs. This can be considered, as an indirect measure of the funds' β (beta).

2.5 Returns

This paper evaluates the returns for the aforementioned funds, those are specified by the following equation:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

In the abovementioned equation (2) r_t is the return in time t, ln is the natural logarithm i.e. logarithm to the base of constant e (Euler's number), P_t refers to the price at time t with P_{t-1} correspondingly being the price at prior time of $t-1$.

As the trading in the US only occurs during the working weekdays the values for weekends and holidays are excluded from the evaluation. The returns have been calculated from the "Adjusted Close" price of each day; this value excludes the dividend accumulation and accounts for any potential splits. This is done by applying appropriate multipliers provided by the Center for Research in Security Prices (CSRP) to the daily closing prices in order to "externalize" the effects of the significant effect that dividends have on ETF prices. This allows to evaluating an amended ETF price that reflects the funds' value after adjusting it for any "external" factors; thanks to that the data set avoids the monthly cyclical pattern of dividend accumulation which makes it significantly easier to evaluate the data.

3. Methodology

3.1 Model

The initial model used to evaluate if there are any statistically influential effects on the funds' performance is an ARIMAX model; this is an extension of the Autoregressive Integrated Moving Average model (ARIMA) allowing for the inclusion of exogenous variables that take the form of additional independent variable in the equation. This allows for the inclusion of lagged values in the model as an explanatory factor. Equation (2) showcases the initial form of the model. Using a methodology similar to that of Müller (2009) the mean return equation is presented below:

$$r_t = \beta_0 + \beta_1 CI_t + \sum_{i=1}^{p} \phi_i \, r_{t-i} + \sum_{j=1}^{q} \theta_j \, \epsilon_{t-j} + \epsilon_t \qquad (3)$$

β_0 denotes the constant, ϕ_i represents the coefficients of the autoregressive terms with r_{t-j} being the lagged values of the time series. θ_j are the coefficients of the moving average terms with ϵ representing the error terms at time *t-j* and *t* respectively. Finally, two versions of the model are employed and evaluated one using the VIX data and other using the Spread data which is denoted by CI_t which represents changes in the value of the indicator.

There are seasonality phenomena that might be of interest and improve the results of this paper's evaluation. The two included seasonality dummy variables are presented in the next subsection.

3.2 Seasonality Dummy

Seasonality denotes the tendency of time series data to display predictable and consistent tendencies that repeat on a regular basis. The existence of seasonality when it comes to stock performance has been observed and evaluated for a long time (Rozeff & Kinney, 1976). Incorporating the evaluation of seasonality into our model further reinforces the examination of the potential sources of external impact on the performance of the funds. This paper employs two "seasonality effects":

1) Monday Effect

The existence of consistent anomalous and abnormal returns reported on the first day of the week has been one of the more puzzling empirical findings for market researchers to understand (Wang et al., 1997). Abraham and Ikenberry (1994) were amongst the first to properly evaluate data pertaining to the "Monday Effect". Their findings indicate that Mondays' returns are positively correlated with the returns observed on the prior trading day (Abraham & Ikenberry, 1994). Those findings are partially contested by Wang et al. (1997); according to the authors the magnitude of the "Monday Effect" differs between the Mondays of the month. Kim and Ryu (2022) evaluate the effect of market sentiment on the prevalence and magnitude of the Monday Effect; using an elaborate sentiment index based on big data and the use of machine learning the authors find that sentiment plays a significant role when it comes to Monday effect. The effect is further affected by changes in sentiment during the non-trading days preceding the first day of the week.

If that is the case detecting the Monday Effect in the data would suggest strongly that confidence plays a role in the ETF performance not only during trading days but also on non-trading days.

2) January Effect

The persistence of the so-called "January Effect" has been observed since the study of Rozeff and Kinney (1976) which was the first to observe that equity markets display consistently higher returns during the first month of the year. Since then vast volume of subsequent research has further confirmed the existence of the anomaly (Moller & Zilca, 2007). Haug and Hirschey (2006) describe the January Effect, as a "real and continuing anomaly in stock market returns and one that defies easy explanation". There is, however, still plenty of research pointing towards the opposite conclusion. Patel (2015) states that the phenomenon is no longer present in international stock returns, neither, does he find any proof of the January Effect in evaluated sub-periods or sub-groups.

The potential existence of such deviation appears to put into question the perfect rationality of investors; detecting the January Effect in the performance of the evaluated ETFs would further provide evidence of their susceptibility to cognitive biases. Incorporating it into evaluation is also worthwhile, due to the fact that as already mentioned the ongoing debate is certainly far from being settled.

It is important to mention that, as this paper evaluates only a singular year the results will only indicate if the January Effect is present in the ETF market for the period 2023/2024. The results cannot be used to either disprove or confirm the general existence of the phenomena, because of the limited scope of the evaluation. Still, integrating it into the model might provide considerable insight, as the discussion on the January Effect is ongoing.

3.3 Updated Model

Incorporating the abovementioned dummies new equation (3) is constructed in order to account for the potential seasonality effects:

$$r_t = \beta_0 + \beta_1 DMonday_t + \beta_2 DJanuary_t + \beta_3 CI_t + \sum_{i=1}^{p} \phi_i \, r_{t-i} + \sum_{j=1}^{q} \theta_j \, \epsilon_{t-j} + \epsilon_t \tag{4}$$

where, $DMonday_t$ is a dummy variable that equals 1 for every Monday return to account for the described Monday Effect. Additionally, $DJanuary_t$ is a dummy variable which equals to 1 for the returns observed between January 1st and January 14th when the effect is most profound (Moller & Zilca, 2007). Still the results cannot prove or disprove the persistence of January Effect, but rather only the potential presence of it during the evaluated period.

3.4 ARIMA Order

In order to conduct evaluation through the ARIMA model the order of the autocorrelation process, the moving average process and the degree of differencing needs to be determined. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) provide information regarding the order of the processes. Their graphs are shown in the Appendix A.1 – A.10

After conducting ARIMA estimation the order of autocorrelation process and differencing is found based on the Akaike Information Criterion and Bayesian Information Criterion. Due to focus on returns additional differencing is not required. The following ARIMA orders were selected for the ETFs:

1) JEPI – ARIMA (0,0,0)
2) DFAC – ARIMA (0,0,0)
3) JPST – ARIMA (3,0,0)
4) JEPQ – ARIMA (0,0,0)
5) MINT – ARIMA (1,0,1)
6) AVUV – ARIMA (0,0,0)
7) DFUV – ARIMA (0,0,0)
8) DFAT – ARIMA (0,0,0)
9) DFUS – ARIMA (0,0,0)
10) ARKK – ARIMA (0,0,0)

3.5 Variance Equation

Utilizing ARIMA-GARCH modeling allows for the evaluation of not only the returns, but volatility as well. To capture time varying volatility n the error term ϵ_t in Equation (3) GARCH (1,1) is employed with its form presented below (4) based on the Bollerselv (1986) representation.

$$\epsilon_t \sim^{iid} N(0, \sigma_t^2) \tag{5}$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$N(0,\ \sigma_t^2)$ is the conditional distribution of ϵ_t with zero mean and the variance of σ_t^2. The conditional variance is determined by its lagged version (σ_{t-1}^2) and the squared values of past errors (ϵ_{t-1}^2).

3.6 Combined Model

Merging the mean model part and variance model part we obtain the model (5).

$$r_t = \beta_0 + \beta_1 DMonday_t + \beta_2 DJanuary_t + \beta_3 CI_t +$$
$$\textstyle\sum_{i=1}^{p} \phi_i\, r_{t-1} + \sum_{j=1}^{q} \theta_j\, \epsilon_{t-j} + \epsilon_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$
$$\epsilon_t \sim^{iid} N(0, \sigma_t^2) \tag{6}$$

In order to ensure positive conditional variance α_0 is assumed to be positive, α_1 and β_1 are assumed to be greater or equal 0; additionally, to ensure stationarity assumption of $\alpha + \beta < 1$ should be true.

3.7 Correlation of the Indicators

Although, VIX and Spread are considered as reliable quantitative predictors of investor confidence it is possible that given the simplicity of the model they might capture the effects of the market returns (Ding et al., 2021). Figure 15 presents the cross-correlation for utilized market indicators and S&P500.

Figure 15:

Cross-correlation of VIX/Spread and S&P500 Returns

Returns ~ VIX	VIX ~ Returns	Retruns ~ Spread	Spread ~ Returns	Lag
-0.737759307	-0.737759307	-0.507559498	-0.507559498	0
-0.020236667	-0.070027982	-0.27722924	-0.085850605	1
0.105051028	0.085086274	0.064419387	0.115977982	2
0.078099916	0.087588744	0.065481155	0.053948997	3
0.008832907	-0.020810307	0.010097523	0.073372429	4
0.072614054	-0.076636844	-0.033097355	0.000188912	5

Note: The table showcases cross-correlation between VIX and S&P500 returns, as well as, Spread and S&P500. The right column denotes the number of lags for a given correlation.

Clearly, there is a significant degree of correlation between the indicators and S&P500 returns, especially for VIX at -0.73. Crucially it appears that the correlation is "simultaneous" so the effect is not lagged. Still, given the fact that the effect is quite substantial, it would be wise to compare the model (6) with one that includes S&P500 returns as an additional variable. The presence of multicollinearity will severely limit the accuracy and predictive power of the model, however, the model will highlight the close association of VIX and S&P500 returns. The secondary model is presented below with all the specifications kept the same with an additional variable SPX_t which denotes the S&P500 returns at time t:

$$
\begin{aligned}
& r_t = \beta_0 + \beta_1 DMonday_t + \beta_2 DJanuary_t + \\
& \beta_3 CI_t + \beta_4 SPX_t + \textstyle\sum_{i=1}^{p} \phi_i \, r_{t-1} + \sum_{j=1}^{q} \theta_j \, \epsilon_{t-j} + \epsilon_t \\
& \sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\
& \epsilon_t \sim^{iid} N(0, \sigma_t^2)
\end{aligned} \tag{7}
$$

The high degree of correlation is not surprising given the fact that S&P500 options are the primary source used for the calculation of VIX. Still, such a high degree of correlation proves cumbersome, as it makes it difficult to disentangle the effects of VIX and S&P500.

4. Hypothesis

The following chapter goes over the proposed hypothesis evaluated in the paper. Those are based on conventional knowledge in the field of behavioral finance which has been summarized in the previous chapters.

Hypothesis 1: Returns of Actively Managed ETF's are affected by investor sentiment

Given the ample evidence pointing towards the significant degree of "irrational" behavior within the realm of the financial markets, it is reasonable to assume that fund managers are not immune to such biases. It is plausible that their decisions in regards to funds portfolio can be influenced by sentiment in turn effecting the ETF price. Chang et al. (2016) find evidence of the disposition effect among mutual fund managers so this implies that they can be affected by multiple cognitive biases such as prospect theory and mental accounting. This is why this paper employs statistical testing in order to verify if the effect of the indicators on fund returns is different from zero.

Although, portfolios of ETFs can be considered, as simply a basket of stock and/or bonds their creation process differs significantly from the way in which an individual investor would create a portfolio. ETF portfolio is created with a notion of a specific concrete goal stated in the prospectus that rarely is modified in any capacity. Brozynski et al. (2006) find conflicting evidence, as to the nature of risk-taking, overconfidence and herding of fund managers. Contradictory evidence might point towards some level of immunity of fund managers towards cognitive biases implying that the effect can potentially be negligible.

Hypothesis 2: Prices of ETFs of a specific characteristic are affected by investor sentiment

It is plausible that only ETFs of certain characteristics are affected by sentiment; ETFs in the sample have different yields and risk exposures. Funds invest in securities of entities with different market capitalization and duration. All of these factors might make certain portfolios more exposed to the effects of sentiment resulting in different effects on the returns of the funds of different characteristics. Such evaluation is crucial, as the number of different types of ETFs is constantly growing, with different profiles and target areas.

5. Results

5.1 VIX Effect

Appendix B.1 – B.10 showcases the full outputs for the estimated coefficients of the model fit, Figure 16 summarizes the result below. Immediately one can see that the effect of VIX is statistically significant at 5% confidence level for all of the funds excluding JPST. While evaluating the signs of the coefficients one can see that for all of them, the corresponding coefficients are negative with the only exception being MINT. This would imply a reverse relationship between the VIX and the returns of the funds. Such findings seem to point towards Hypothesis 1, with the greater implications discussed later in Chapter 6.

Figure 16:

Summarized VIX effect on the funds

Fund	VIX Effect	Monday Effect	January Effect
DFAC	-0.110013***	0.002407***	-0.001514
ARKK	-0.231670***	0.009557***	-0.010974*
AVUV	-0.131021***	0.002124	-0.00547*
DFAT	-0.129899***	0.002352*	-0.005007*
DFUS	-0.112955***	0.00249***	-0.000578
DFUV	-0.095766***	0.002047***	-0.002228
JEPI	-0.059829***	0.001753***	0.00014
JEPQ	-0.088432***	0.002793***	0.0004
JPST	-0.000354	-0.000107**	0.00004
MINT	0.00105***	-0.000089***	0.000082**

Note: The table presents summarized model outputs showcasing the results of the VIX effect on the returns of the evaluated funds. significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Turning one's attention towards the results for the dummy variables the implications for the Monday Effect can be observed for all but two funds; those being AVUV and DFAT. However, for January Effect results do not point towards any strong suspicion of its effects; AVUV is the only fund that displays the January Effect at the conventional 5% confidence level. The null can be rejected for JPST, DFAT and ARKK only at a 15% confidence level, this does not seem to indicate the existence of the January Effect in our sample. Although the evaluation focuses only on a single year there has been a growing volume of research pointing towards a similar conclusion of the January Effect being no longer present within the US equities markets (Gu, 2002; Patel, 2016).

5.2 Spread Effect

Full outputs for the model employing Spread are presented in Appendix B.1 – B.10, Figure 17 summarizes the estimated coefficients below. All the presented coefficients are statistically significant. The effect for MINT and JPST is positive, whereas, for the rest of the funds it is negative; this is not surprising considering that those are funds focused on investment grade debt. Once again the findings seem to point towards Hypothesis 1, as well as, Hypothesis 2.

Figure 17:

Summarized Spread effect on the funds

Fund	Spread Effect	Monday Effect	January Effect
DFAC	-0.231998***	0.001901**	0.000252
ARKK	-0.465493***	0.008339***	-0.006726
AVUV	-0.332433***	0.001362	-0.00227
DFAT	-0.323162***	0.001596	-0.002007
DFUS	-0.219377***	0.001949**	0.001058
DFUV	-0.22916***	0.001684*	0.000088
JEPI	-0.078918***	0.001334***	0.000864
JEPQ	-0.134271***	0.001762**	0.001835
JPST	0.004643***	-0.000106**	-0.000001
MINT	0.00309***	-0.000073**	0.000005

Note: The table presents summarized model outputs showcasing the results of the Spread on the returns of the evaluated funds. significance levels are denoted ***$p < 0.05$, **$p < 0.10$, *$p < 0.15$.

For the Monday Effect dummy the results are quite mixed; at the conventional 5% confidence level the coefficients are significant for just JEPI and ARKK. At the 10% confidence level JPST, MINT, JEPQ and DFUS are also significant, at 15% confidence level DFUV becomes significant. Turning towards January Effect no coefficient is statistically significant.

5.2.1 Comparison with S&P500

Additionally, it is worthwhile to compare the effect VIX and Spread have on S&P500 during the corresponding period. The model's parameters are kept with S&P500 returns being used rather than ETF returns. Results are presented in Appendix B.11 with the point estimate of -0.10 for the model employing VIX and -0.20 for the one employing Spread. This implies that the effects of confidence are more pronounced for DFAC, ARKK, AVUV, DFAT, DFUS then the ones observed for S&P500; consequently, the effects confidence has for DFUV, JEPI, JEPQ, MINT and JPST are less pronounced than for S&P500. This provides interesting observation with exactly a 50/50 split in terms of the greater and lesser impact of confidence on the observed ETFs.

5.3 Robustness Checks

This section presents several robustness measures in order to further, verify the results and ensure their correctness. Thanks to that the obtained results can be evaluated with much greater confidence. The validity of the results was investigated by evaluating the Stationarity, Residuals and Information Criteria of utilized data and models.

5.3.1 Stationarity

As already mentioned in a previous part the data sample has been constrained to one year in order to ensure stationarity. This is also why the returns are evaluated rather than simply adjusted closing prices, as is a common practice while evaluating financial data. In order to ensure stationarity an Augmented-Dickey Fuller Test has been conducted; as presented in Appendix C.1 – C.10 the results rule out the possibility of existence of the unit root for all of the ETFs. The condition of stationarity is highly important in order to avoid spurious regression; otherwise, the findings might be misleading pointing towards a "phantom" relationship. Stationarity ensures that the time series data has constant mean, variance and autocorrelation, this however, is often not the case for economic and financial data which is prone to trends (Ventosa-Santaulària, 2009). This is clearly a case for the evaluated ETFs, even after employing the logarithmic return transformation and differentiating the data for periods larger than one year it is non-stationary. Those are the effects of the global exogenous economic and political circumstances leading to vast shifts in variance for the evaluated financial instruments.

5.3.2 Residual Analysis

Conducting the ARCH-LM test showcased in Appendix C.11 clearly does not provide enough evidence to reject the null hypothesis pointing strongly towards the lack of autocorrelation of the residuals in the samples. The only expectation is JEPQ (VIX) for which the test is statistically significant at the conventional 5% significance level. This implies that for the rest of the funds, the residuals can be considered as a "white noise" without any dependencies between the values. One could consider that GARCH (1,1) is not sufficient in capturing the developments of conditional volatility. Employing a sign bias test reveals the possibility of the existence of the leverage effect for MINT. This occurs when there exists a negative relationship between asset value and volatility, implying that negative shocks increase the volatility more than positive shocks of equal magnitude (Black, 1976; Christie, 1982). It would be possible to capture such effects using a modified GARCH model, however, the focus of this paper is on the effects present in the mean equation. Due to that in order to keep the estimation consistent and simple GARCH (1,1) has been deemed to be sufficient for the analysis.

Additionally, the Adjusted Pearson Goodness of Fit Test, for all the funds, yields results that do not allow for the rejection of the null hypothesis at the conventional significance levels implying an appropriate predictive power of the model.

5.3.3 Information Criteria

Creating two model variations allows for a comparison of the predictive power of the models employing VIX and Spread in order to evaluate which parameter might be used to better evaluate the behavior of funds. Utilizing certain selection criteria allows for an inspection of the two versions of the model. Interestingly for both of the models, employing VIX and Spread, the information criteria presented in the table are very similar. For the majority of the funds the model employing VIX appears to be able to convey slightly more information; nonetheless, for JPST and MINT the Spread appears to produce slightly more appropriate model. This is not surprising as mentioned before those are the two funds primarily focused on investment grade debt which will be much more susceptible to interest rate shifts. Nonetheless this does showcase that both versions of the model are quite comparable, with the VIX displaying higher quality estimation for equity funds and Spread for debt funds. The same conclusions can be drawn from evaluating log-likelihood values presented in Appendix B.1 – B.10. Based on that it is reasonable to assume that both VIX and Spread are in general quite comparable in their effectiveness as a proxy for investor confidence with VIX being a slightly more appropriate measure for equity focused instruments.

Figure 18:

AIC and BIC for the estimated models

	Akaike	Bayes
DFAC (VIX)	-7.554	-7.4557
DFAC (SPREAD)	-7.1589	-7.0606
ARKK (VIX)	-5.0303	-4.9320
ARKK (SPREAD)	-4.8431	-4.7448
AVUV (VIX)	-6.2248	-6.1265
AVUV (SPREAD)	-6.1015	-6.0032
DFAT (VIX)	-6.3456	-6.2472
DFAT (SPREAD)	-6.2049	-6.1066
DFUS (VIX)	-7.7416	-7.6433
DFUS (SPREAD)	-7.21	-7.1117
DFUV (VIX)	-7.256	-7.1576
DFUV (SPREAD)	-7.0557	-6.9574
JEPI (VIX)	-8.6485	-8.5502
JEPI (SPREAD)	-8.1441	-8.0458
JEPQ (VIX)	-7.8072	-7.7088
JEPQ (SPREAD)	-7.3625	-7.2641
JPST (VIX)	-12.922	-12.782
JPST (SPREAD)	-13.036	-12.896
MINT (VIX)	-13.688	-13.562
MINT (SPREAD)	-13.603	-13.477

Note. This Table presents Akaike Information Criterion (AIC) and Bayesian Information Criterion values for the estimated models.

6. Results Discussion

Given the results there appears to be strong evidence pointing towards Hypothesis 1; for both of the models, there is a strong relationship between the performance of fund returns and changes in both VIX and Spread. There exists a negative relationship between the changes in the indicators and the returns. This implies that increases in the VIX index result in decreases in the ETF returns; this relationship is true and statistically significant for all of the funds excluding MINT and JPST, both of these display a statistically significant positive relationship and are debt-funds that focus on investment grade debt. The negative effect is most profound on funds specializing in small-cap value equity; this intuitively can easily be understood, as those are considered much riskier and the investors can be easily “spooked” from allocating their assets to such companies. This would imply that during periods of lower confidence (higher index values), the performance of equity-focused ETFs decreases; at the same time, debt-based funds perform significantly better. This is in line with findings presented by Böni and Manigart (2022) who find that both market volatility and expected market volatility are positively correlated with the performance of private debt funds. There have been many answers proposed as to why this is the case, however, no explanation has been found that can fully understand this phenomenon (Block et al., 2024). This is especially interesting given the fact that Munday et al. (2018) find that private debt funds have outperformed the leveraged loan and high-yield bond markets since 2004. Böni and Manigart (2022) similarly to this paper evaluate the performance at the fund level; they raise the point that it might be worth evaluating whether the private debt firm or rather specific individuals or groups of individuals in the firm drive performance.

Similarly, the model employing Spread indicates a statistically negative relationship for all of the funds other than MINT and JPST, both of which once again have a positive relationship. Increases in Spread can be considered, as representing decreases in market confidence, due to decreased demand for riskier bonds and market-wide turn to more "secure" investments. Interestingly, Böni and Manigart (2022) find that private debt funds are able to anticipate the spread shifts allowing them to realize abnormal returns.

While comparing the effects the evaluated indicators have on S&P500 to their effects on ETFs the range of "impact" is quite interesting; it appears the sensitivity varies greatly between the evaluated ETFs. This would imply that the effect is quite varied with certain funds displaying higher sensitivity and others lower sensitivity to changes in confidence. The differences are profound even between ETFs of similar characteristics; pointing towards the possibility outlined by Böni and Manigart (2022) that private debt firms or individual managers can potentially have a persistent effect on ETF performance.

In light of all of these findings, it appears that VIX and Spread indeed have a significant effect on the performance of the ETFs. The relationship is statistically significant for at least one of the indicators for all of the evaluated funds which is indicative that the effect is omnipresent within the ETF market. This effect is further reinforced due to the fact that obtained coefficients are closely mirrored; all the obtained coefficients have the same sign and the coefficients obtained in the Spread model are approximately twice the ones for the VIX model.

However, it is important to highlight that a close relationship between changes in VIX and S&P500 returns makes it problematic to disentangle the effects of the two.

Additionally, there appears to be some evidence pointing towards the existence of the Monday Effect within the ETF market. For most funds, the results are statistically significant at the conventional 5% significance level and point towards the presence of the phenomena. This would imply that the phenomena also exists within the ETF market and has an impact on the returns of the traded ETFs.

On the other hand, there appears to be no indication pointing towards the presence of the January Effect within our sample, as only three VIX models are statistically significant at a 15% significance level. Given the fact that the sample data consists only of a single January, it is not enough to fully disprove the existence of the January Effect. Still, it does indeed imply that there appears to be no statistical effect on ETFs during January 2024. It is in line with the large volume of research that indicates that the January Effect is becoming much less pronounced nowadays and is not as impactful anymore (Patel, 2016).

As already mentioned there appears to also be significant evidence pointing towards Hypothesis 2; debt funds included in the sample appear to have a reverse relationship than the one present for other ETFs. PIMCO and MINT appear to yield higher returns in periods of lower confidence. It is clear that the debt funds behave in a significantly different fashion than the rest of the funds. Those funds appear to display a opposite relationship to the one found for the remaining of equity focused ETFs potentially indicating a substantial diversification opportunity for the investors willing to hedge their portfolio against market risk.

Given the abovementioned findings, it becomes apparent that investors must evaluate market sentiment when deciding to invest in different types of ETFs; this means that portfolio creation needs to be approached with additional conditions in mind in order to be able to maximize the returns. The classical approaches such as, for example, CAPM operate on the basis of rational investors, those investors should be indifferent towards the market sentiment and have a consistent risk factor. If this is not the case portfolio-creation process needs to be extended to include those factors in its deliberation. Especially, considering the composition of ETFs and their type becomes crucial in order to ensure desirable conditions. Given that the abovementioned effects differ in strength between equity funds of different profiles it is plausible that the strength of the effect might be dependent on the management structure of the given ETF. The findings in this paper give credibility to the Behavioral Asset Pricing Model; it is an extension of the well-known Fama and French Three-Factor and Fama and French Four-Factor models. It expands those by including cognitive factors, in such a model, investor confidence will play a significant role in the way in which assets are valued (Statman, 2008). Shifts in confidence will conversely change the valuation and what the Statman et al. (2008) refer to as "subjective" risk and in turn will influence asset valuation and expected returns. If investors wish to fully capture the effects of that phenomenon they need to account for it during the portfolio creation process.

6.1 Secondary Model

Evaluating the model (7) provides interesting additional insight; the results provided in Appendix B.12 indicate that a significant part of the effect that is captured by VIX is tied to the changes in the returns of the S&P500. Including the market returns into a model reduces the number of funds that appear to display a statistically significant relationship with the changes in VIX. Still, such a relationship is present for JEPI, JEPQ and MINT. The model employing Spread results displays a statistically significant relationship for seven of the funds. For all the funds other than MINT there is a statistically significant relationship between S&P500 returns and fund returns.

The close correlation between the two variables makes it difficult to disentangle their effects resulting in multicollinearity and reducing the accuracy of the regression estimates (Mansfield & Helms, 1982). This is especially problematic while trying to evaluate the relationships between sets of variables. The introduced large variances of coefficients make it difficult to correctly evaluate the model and its components. Still, the coefficients for VIX and Spread effects have the same signs, as the ones obtained in the model (6). Although no concrete considerations can be drawn this highlights the issue of the VIX Index and its close association with S&P500 returns.

7. Comparison with Other Research

As mentioned multiple times throughout this paper the volume of literature concerned with ETFs is severely limited; still, it is possible to compare the findings presented in this paper with ones evaluating the effect of investor sentiment on stock returns and mutual funds. Although the nature of the investments differs substantially it still allows one to look at the greater market-wide picture and evaluate potential similarities and differences in behavior.

Nguyen et al. (2018) find that returns of mutual funds are positively correlated with investor confidence, their study focuses on the quickly growing economies of India and Pakistan. Statman and Fisher (2002) conclude similar evaluation within the US economy; their findings are similar, the researchers find a positive and statistically significant relationship between changes in consumer confidence and concurrent stock returns. However, it appears that the relationship is negative for one month of future returns of Nasdaq and small-cap stocks (Statman & Fisher, 2002). The main concern with the abovementioned study is its utilization of consumer rather than investor confidence; still, the authors conclude that the relationship between consumer confidence and investor confidence is positively correlated and statistically significant. Those findings are partially replicated by Bathia and Bredin (2016), according to the researchers US growth stocks are significantly negatively affected by the changes in sentiment. However, their findings conflict with the findings presented in this paper, as the researchers find a negative effect of confidence on the aggregate market returns. This is an interesting discrepancy, as the researchers evaluate aggregate market returns based on Kenneth R. French library data rather than S&P500. Additionally, the researchers employ a forward-looking panel, fixed-effect model.

The findings pointing toward a negative relationship between sentiment and future market returns are contested by Brown and Cliff (2004). Based on the vector autoregressive framework the relation between sentiment and near-term stock returns is evaluated. The research finds little evidence of short-run predictability in returns; still, the findings are consistent with the ones presented in this paper, as the researchers find a strong relation between current market returns and sentiment. Similarly, Canbaş and Kandır (2009) evaluate the effect of sentiment on Turkish mutual fund and stock returns; the findings point towards the lack of forecasting power of sentiment on future returns. Based on the VAR model employing six investor proxies the researchers find no statistically significant relationship between the confidence indicators and future returns.

Smales's (2017) findings differ significantly from the ones presented above; evaluating US stock returns the findings point towards a significant positive relationship between market-wide equity returns and market-wide sentiment. The research employs, similarly to this paper, VIX amongst other indicators of investor confidence. Interestingly the paper also finds the proof of, what can be called, "modified" Prospect Theory; according to the findings, the decreases in confidence have a stronger impact on the returns than equivalent increases in confidence.

On the other hand, Huang et al. (2014) find that the relationship is only significant for specific industries and is not universal for the whole market. Additionally, they consider the bullish and bearish markets differently, with a consequent evaluation of twelve different market sectors (Huang et al., 2014). Those findings partially overlap with the ones presented in this paper, as clearly, the effect differs in both strength and direction between the ETFs of different profiles.

Clearly, none of these research papers focus on ETFs specifically, however, it is still clear that there are a significant number of conflicting opinions, as to the effect of investor confidence on the performance of different market instruments. Such different findings are quite interesting, as they differ substantially from each other and no comprehensive study has been conducted to understand such discrepancies. Where other behavioral theories have been studied thoroughly and provided consistent results it appears that the effect of investor confidence differs greatly between countries, asset classes and financial instruments. This is not the case for e.g. cognitive dissonance, theory of regret, prospect theory and a vast number of other behavioral factors. It is possible that an important characteristic that might play a significant role in the effect of sentiment on returns is omitted. It is reasonable to assume that more consideration should be given to differences in liquidity and trading costs. Investor confidence is closely tied to trading frequency and has been one of the answers to the "active investing puzzle" with highly confident investors having aggressive stock trading strategies and investing in actively managed funds (Hirshleifer, 2015). As ETFs are highly liquid and generally possess lower trading costs than mutual funds it is plausible that the effect of confidence will differ between different equity and asset classes. Interestingly there is evidence pointing towards the ETF market being influenced differently by behavioral phenomena than other financial instruments. Rompotis (2018) is one of the few papers that focuses solely on the ETF market and finds that, surprisingly, ETFs are not prone to herding regardless of market conditions and market-wide volatility. Additionally, He finds a significant correlation between ETFs' return dispersion and trading volume. This partially goes against convenient financial wisdom of the negative effect of high turnover on the returns, but once again might point towards the unique features of ETFs that have not been properly evaluated.

The volume of research is severely limited, but it does appear that the high liquidity of ETFs influences the appropriate trading strategy that should be employed by investors wishing to engage with them. Although they share many similarities with mutual funds they do possess important features which make them uniquely distinct. It is those features, such as liquidity, low fees, transparency, and potential tax advantages that have fueled the unprecedented growth of the ETF market (Lettau & Madhavan, 2018). Additionally, the ETF market has been expanding beyond traditional equity-based funds, with a plethora of fixed income, commodities, currency, volatility, multi-asset class structures, and "smart beta" funds. Many of those are erasing the traditional active/passive demarcation, providing what can be considered as, "hybrid" funds.

8. Limitations and Areas for Further Research

VIX Index is considered to measure the predicted volatility in the market and as such gauge the sentiment of market participants (Marquit, 2024). Similarly, bond spreads have often been regarded, as one of the more accurate predictors of market-wide sentiment expectations. Their quantitative nature is another highly appealing factor, as it makes it significantly easier to evaluate them, as already mentioned working with qualitative data is in itself tricky, especially when considering daily data. This is why this paper utilizes those measures as sentiment proxies; still, the question arises if those measures truly capture market-wide sentiment or are simply a reflection of market conditions which in turn those conditions drive the sentiment. Such an evaluation is beyond the scope of this paper, however, conducting an evaluation that takes into account questioners and surveys might shed more light on the subject. Psychologists have developed a significant number of methods that allow for the "de-bias" of survey data and the utilization of it in quantitative settings (Tyszka, 1999). Still, such surveys are time-consuming and expensive to conduct limiting the potential frequency of their publication.

The time period covered in this paper is also quite small limiting the number of observations utilized in the evaluation. Comparing different periods might allow for more dependencies to be discovered and evaluation of the relationship during different market conditions. This is also connected with the recent “boom” in the ETF industry which has grown rapidly in recent years.

Another matter worth paying attention to is the fact that it might be also possible for the ETF price to diverge from NAV, due to shifts in supply and demand. Although such deviations are often very small they might still have small-scale effect of the ETF returns. This being the case means that the performance might be affected not only by the bounded rationality of the fund managers but also by the bounded rationality of the fund investors. This is partially disputed by the findings of Ülkü and Rogers (2018), although their research is concerned with the Monday Effect they find that individual investors do not contribute to the Monday Effect in stock returns, but rather they actually trade against it; their empirical findings point towards the institutional investors being the driving force behind the phenomena.

Evaluation of the persistence of volatility is another area worth paying attention to; Kumari & Mahakud (2015) find that previous market biases and miscalculations e.g. herding behavior, are closely tied with the impact of subsequent future volatility patterns. If the volatile periods within the market influence the future perception of volatility the investors need to approach their risk valuation differently than conventional financial wisdom would decree. Importantly it appears that the effect of volatility clustering differs substantially between the markets so results cannot be easily replicated between different countries and investment vehicles.

Given the quickly growing importance of ETFs in the current financial world it becomes paramount for the market researchers to analyze them more in-depth. So far the literature present is still at an early stage with many areas still left unexplored; especially, considering the diverse landscape of ETFs that is populated by funds of much greater variety in terms of scope and goals than their more traditional counterparts (Lettau & Madhavan, 2018). Considering that behavioral approaches to finance are becoming increasingly “mainstream” further evaluation of ETFs through this lens is needed; however, it should not be limited in scope, as ETFs are new inventions even to classical finance, with many voicing their concerns about potential “overtrading” due to the high liquidity and potential to propagate liquidity shocks (Ben-David et. al., 2017; Lettau & Madhavan, 2018).

Another point that is worth considering is the potential application of Shefrin and Statman's (2000) Behavioral Portfolio Theory to ETF portfolio creation. It argues that market participants do not, in fact, create their portfolios according to long-established mean-variance portfolio theory, but rather based on a goal-based approach (Statman, 2008). Investors have different aspiration levels that they take into account when developing their portfolios and depending on their emotions and perceptions they can create vastly different combinations of portfolios. In behavioral portfolio theory investors do not view their portfolio, as a whole, but rather as distinct mental layers in a pyramid of assets, where different levels are attributed to different sets of objectives and aspirations. Certain layers could be considered a shield that is designed to prevent an investor from falling into bankruptcy, whereas others might be considered "ability" levels that give an investor a chance to improve their material situation. Quite recently, a new version of behavioral portfolio theory emerged, called mental accounting portfolio. This version combines both the behavioral portfolio of Sherfin and Statman (2000) and the mean variance portfolio of Markowitz (1952) (Das et al., 2010). According to this theory, investors allocate their assets into different accounting layers, where different layers correspond to different goals of the individual (Rent, Insurance Payment, Holiday Fund etc.). Then individuals create a mental probability of reaching the given goal, after which each of the layers becomes a sub-portfolio which is optimized according to the rules of mean-variance portfolio theory using an appropriate combination of assets (Statman, 2008). Given the fact that ETF managers' compensation is directly related to the performance of the fund, it is quite reasonable to assume that they might indirectly assign the goals to the managed ETF. This way it might connect the two sides of the ETF, investors and managers.

Whereas the fact that individuals create sub-portfolios for given goals based on subjective criteria has been thoroughly established within the field of behavioral economics, the mental accounting portfolio theory is definitely not as widespread as the behavioral portfolio theory. It might shed significant insight into the way in which ETFs operate.

It is paramount that more analysis is conducted on the ETF market; the proliferation of ETFs as an investment vehicle is slowly reshaping traditional finance. There is a danger of ETFs being a source of systemic risk, due to potential feedback effects of the instrument value deviating from the market values of the underlying assets (Bhattacharya & O'Hara, 2018). This can result in potential volatility shocks during periods of heavy trading. If sentiment has a significant effect on trading volume it is crucial that its effects on ETFs are studied more in-depth.

Additionally, much greater focus needs to be devoted to studying the behavior of the debt funds; similarly, there has been little research done as to the flow patterns displayed by them. Based on the findings in this paper it is clear that those funds differ in their behavior to their equity counterparts and such most likely ought to be evaluated separately.

9. Summary

The growing importance of ETFs as an investment pooling vehicle increases the importance of evaluating their performance and the factors that influence their behavior. With the growing focus on the behavioral aspects of investment management, the financial field is beginning to assess the impact of bounded rationality on the decision-making process of investors (Pompian, 2011). Given the limited research conducted on the behavior and inner workings of ETFs, this paper evaluates the impact of confidence indicators on the returns of actively managed ETF funds.

The study employs ARIMAX-GARCH models, two versions of the model are used, both utilizing different confidence indicators. The first specification's exogenous variable is the Cboe Volatility Index (VIX) a commonly used proxy aimed at gauging market sentiment and outlook. The second specification utilizes ICE BofA US High Yield Index Option-Adjusted Spread (Spread), allowing for the sentiment to be measured based on the market-wide risk appetite. This paper evaluates the ten biggest US-listed actively managed ETFs; the funds differ significantly in terms of the profile and strategy allowing for a varied sample. The model also includes two seasonality dummies that are aimed at capturing the so-called Monday Effect and January Effect.

The findings contribute to the existing literature as follows. This paper finds a statistically significant effect of both VIX and Spread on the returns of all of the funds; for eight out of ten funds, the point estimate is negative implying that increases in VIX and Spread (i.e. decrease in investor confidence) lead to lower returns. For the remaining two, both of which are debt funds, the estimated coefficient is positive; this implies that debt funds start to generate higher returns during periods of lower confidence. Those findings are in line with the findings of Böni and Manigart (2022). However, evaluation of a second model that includes S&P500 returns, as an additional variable showcases a strong correlation between changes in VIX and S&P500 returns indicating that a significant portion of the effect captured by VIX might be attributed to market returns. Additionally, the paper finds evidence of the persistent Monday Effect within the ETF market, with the majority of the funds displaying a statistically significant effect of the phenomenon.

Those findings contribute to the field by bringing to light the potential of behavioral effects influencing ETF performance; the existing literature is quite scant in terms of evaluating ETFs through a behavioral lens. The limited research primarily has focused on herding within the field (Chen et al 2011; Rompotis 2018; Madura & Richie 2010); the less-than-abundant literature that focuses on confidence and fear evaluates their impact on mutual funds (Smales 2017; Chang et al. 2016). Such research is already quite limited with the evaluation of ETFs being almost completely overlooked. This paper adds value to the existing discussion of behavioral finance and the ETFs market which has been growing rapidly in recent years.

Still, these findings suffer from two main limitations; the evaluated sample is quite limited and limitations of used indicators. Further research could analyze a larger data sample and utilize a different set of proxies for investor confidence, as well as, controlling for different characteristics of the funds through panel regression. This would provide additional information on the drivers of fund behaviors.

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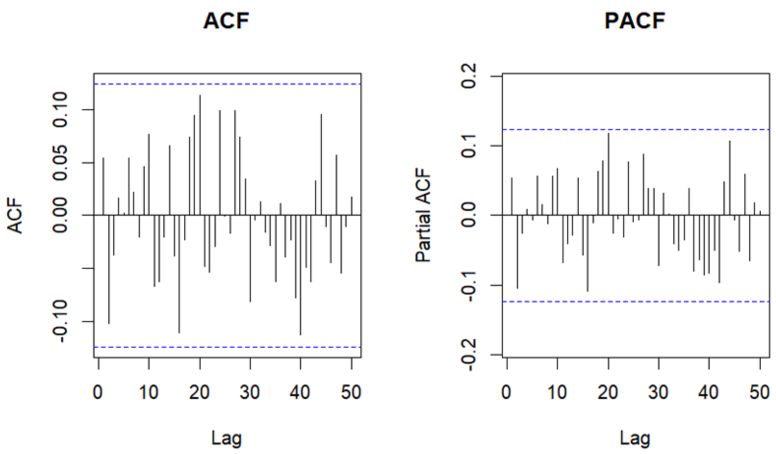
APPENDIX A

Result Tables

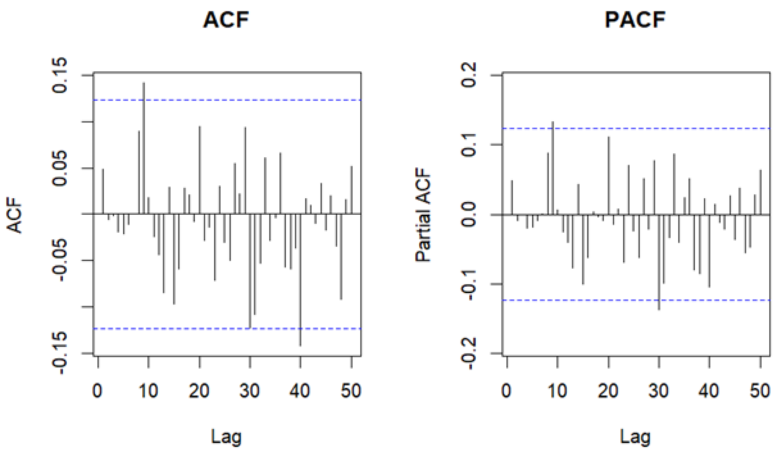
A.1 ACF and PACF

Table A.1: ACF and PACF of DFAC



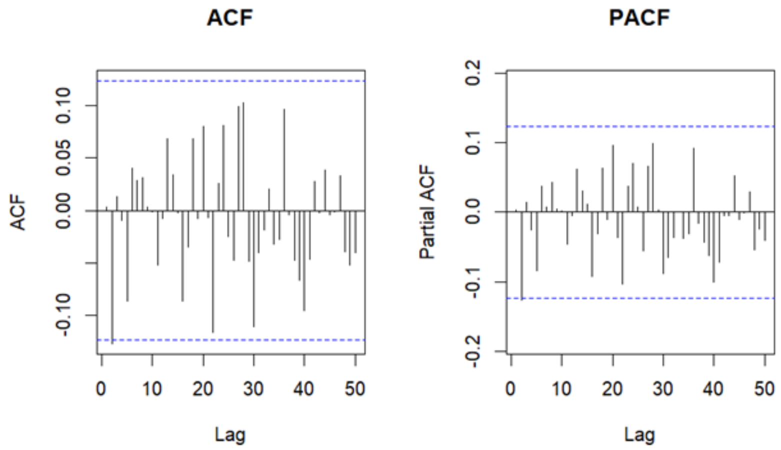
Note. Autocorrelation function and Partial autocorrelation function of returns of DCAF

Table A.2: ACF and PACF of ARKK



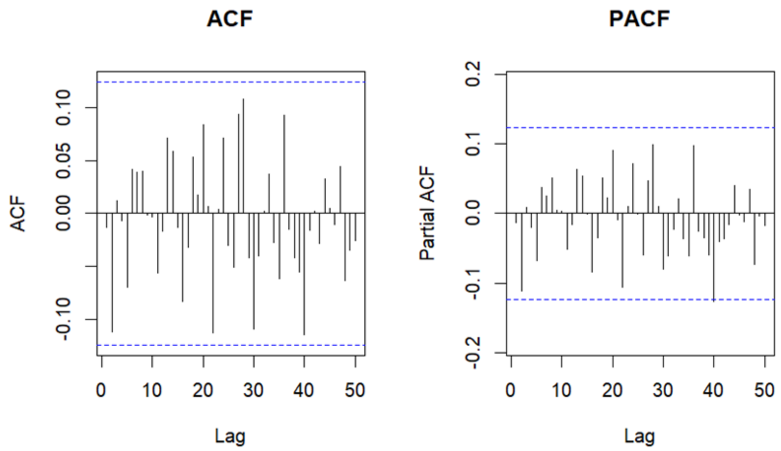
Note. Autocorrelation function and Partial autocorrelation function of returns of ARKK

Table A.3: ACF and PACF of AVUV



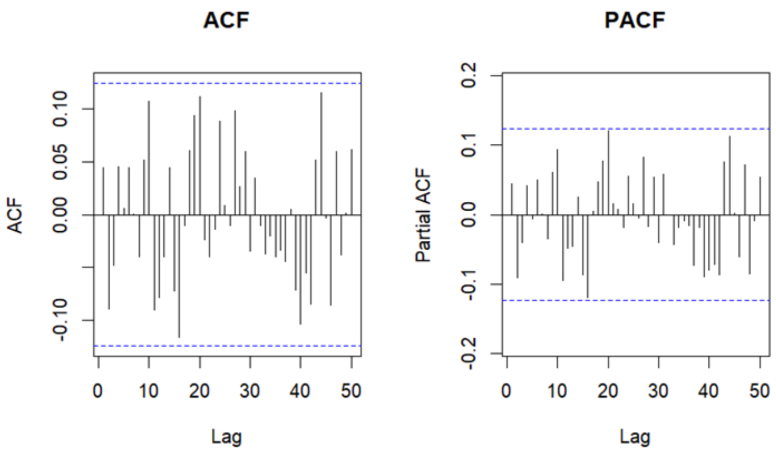
Note. Autocorrelation function and Partial autocorrelation function of returns of AVUV

Table A.4: ACF and PACF of DFAT



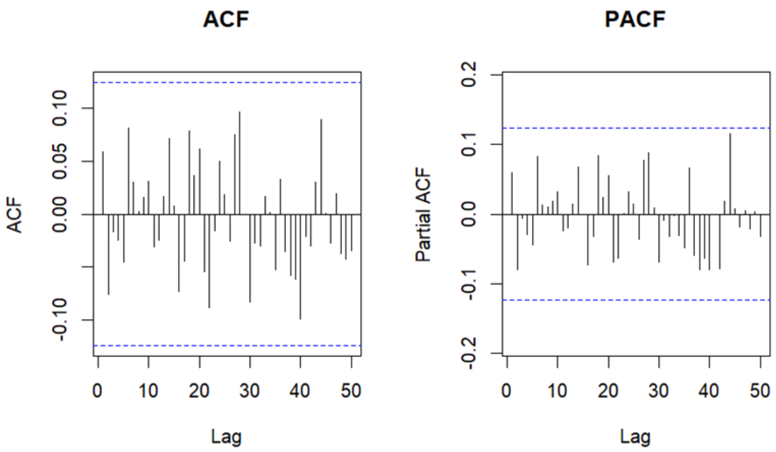
Note. Autocorrelation function and Partial autocorrelation function of returns of DFAT

Table A.5: ACF and PACF of DFUS



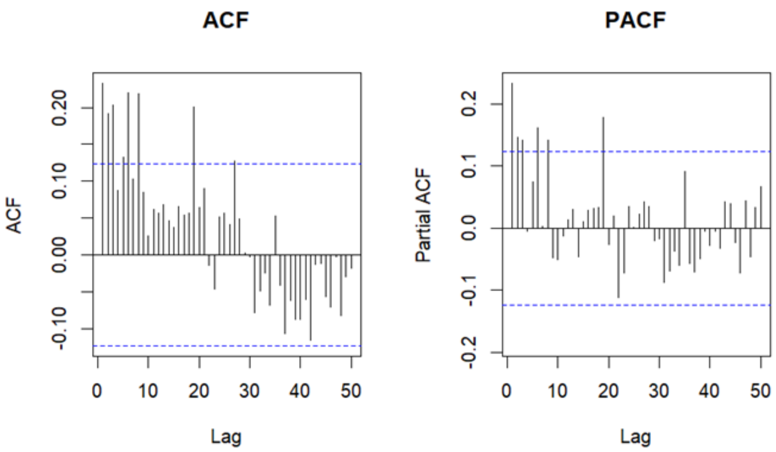
Note. Autocorrelation function and Partial autocorrelation function of returns of DFUS

Table A.6: ACF and PACF of DFUV



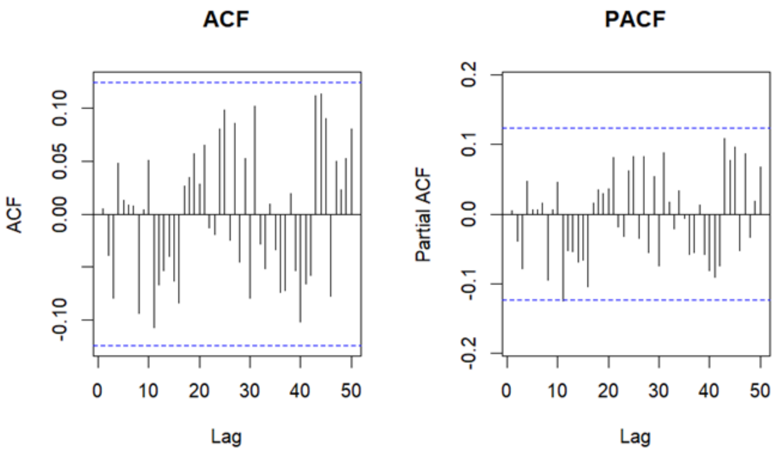
Note. Autocorrelation function and Partial autocorrelation function of returns of DFUV

Table A.7: ACF and PACF of JEPI



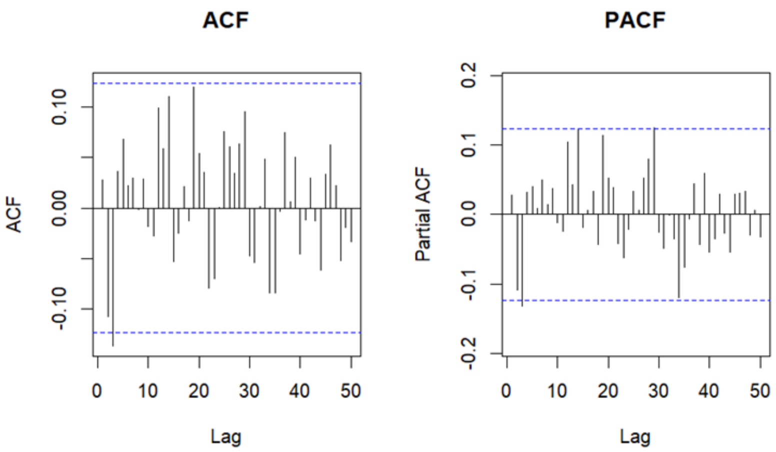
Note. Autocorrelation function and Partial autocorrelation function of returns of JEPI

Table A.8: ACF and PACF of JEPQ



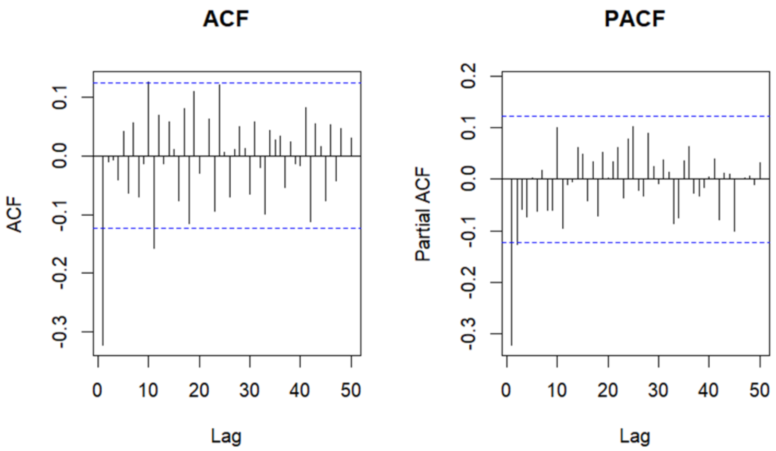
Note. Autocorrelation function and Partial autocorrelation function of returns of JEPQ

Table A.9: ACF and PACF of JPST



Note. Autocorrelation function and Partial autocorrelation function of returns of JPST

Table A.10: ACF and PACF of MINT



Note. Autocorrelation function and Partial autocorrelation function of returns of MINT

APPENDIX B

B.1 Estimation Results

Table B.1 VIX and Spread effect on DFAC

	VIX	SPREAD
mu	0.000337	0.000127
	(0.000371)	(0.000465)
mxreg1	-0.110013***	-0.231998***
	(0.006226)	(0.022923)
Monday Effect	0.002407***	0.001901**
	(0.000839)	(0.00108)
January Effect	-0.001514	0.000252
	(0.001799)	(0.002385)
omega	0.000002	0
	(0.000002)	(0.000001)
alpha1	0.094119***	0.000461
	(0.000296)	(0.000507)
beta1	0.841627***	0.997262***
	(0.036878)	(0.000802)
LogLikelihood	955.027	905.4438

Note. Results for DFAC of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***$p < 0.05$, **$p < 0.10$, *$p < 0.15$.

Table B.2 VIX and Spread effect on ARKK

	VIX	SPREAD
mu	-0.000668	-0.001182
	(0.001345)	(0.00148)
mxreg1	-0.231670***	-0.465493***
	(0.022792)	(0.073048)
Monday Effect	0.009557***	0.008339***
	(0.003132)	(0.003437)
January Effect	-0.010974*	-0.006726
	(0.006817)	(0.007551)
omega	0	0.000001
	(0.000002)	(0.000002)
alpha1	0	0.000066
	(0.000637)	(0.000903)
beta1	0.999000***	0.996801***
	(0.001031)	(0.001013)
LogLikelihood	638.3054	614.8063

Note. Results for ARKK of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.3 VIX and Spread effect on AVUV

	VIX	SPREAD
mu	0.000459	0.000155
	(0.0007)	(0.000790)
mxreg1	-0.131021***	-0.332433***
	(0.012209)	(0.039049)
Monday Effect	0.002124	0.001362
	(0.001637)	(0.001834)
January Effect	-0.00547*	-0.00227
	(0.003157)	(0.004020)
omega	0.000014***	0
	(0.000001)	(0.000001)
alpha1	0.103263***	0
	(0.022489)	(0.001512)
beta1	0.776889***	0.998999***
	(0.037821)	(0.001415)
LogLikelihood	788.2176	772.7356

Note. Results for AVUV of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.4 VIX and Spread effect on DFAT

	VIX	SPREAD
mu	0.000287	-0.000006
	(0.000666)	(0.000749)
mxreg1	-0.129899***	-0.323162***
	(0.011545)	(0.036983)
Monday Effect	0.002352*	0.001596
	(0.001558)	(0.001740)
January Effect	-0.005007*	-0.002007
	(0.003053)	(0.003836)
omega	0.000014***	0
	(0.000001)	(0.000001)
alpha1	0.092581***	0
	(0.021405)	(0.001180)
beta1	0.765912***	0.998998***
	(0.038287)	(0.001052)
LogLikelihood	803.3684	785.7149

Note. Results for DFAT of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.5 VIX and Spread effect on DFUS

	VIX	SPREAD
mu	0.00048	0.000242
	(0.000341)	(0.000453)
mxreg1	-0.112955***	-0.219377***
	(0.005702)	(0.022334)
Monday Effect	0.00249***	0.001949**
	(0.000770)	(0.001052)
January Effect	-0.000578	0.001058
	(0.001591)	(0.002327)
omega	0.000003***	0
	(0.000000)	(0.000001)
alpha1	0.090762***	0.000058
	(0.01863)	(0.000727)
beta1	0.802378***	0.9987***
	(0.034080)	(0.000655)
LogLikelihood	978.5746	911.8561

Note. Results for DFUS of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.6 VIX and Spread effect on DFUV

	VIX	SPREAD
mu	0.000325	0.00003
	(0.000431)	(0.000491)
mxreg1	-0.095766***	-0.22916***
	(0.007517)	(0.024273)
Monday Effect	0.002047***	0.001684*
	(0.000976)	(0.001140)
January Effect	-0.002228	0.000088
	(0.001896)	(0.002495)
omega	0.000005***	0
	(0.000000)	(0.000001)
alpha1	0.104687***	0
	(0.020387)	(0.001540)
beta1	0.771661***	0.999***
	(0.038069)	(0.001435)
LogLikelihood	917.6227	892.493

Note. Results for DFUV of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.7 VIX and Spread effect on JEPI

	VIX	SPREAD
mu	0.000146	0.000186
	(0.000217)	(0.000260)
mxreg1	-0.059829***	-0.078918***
	(0.004042)	(0.013874)
Monday Effect	0.001753***	0.001334***
	(0.000505)	(0.000644)
January Effect	0.00014	0.000864
	(0.000993)	(0.001094)
omega	0.000001***	0.000002
	(0.000000)	(0.000002)
alpha1	0.072336***	).164979****
	(0.014337)	(0.050426)
beta1	0.792237***	).741314****
	(0.031478)	(0.042055)
LogLikelihood	1092.391	1029.089

Note. Results for JEPI of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.8 VIX and Spread effect on JEPQ

	VIX	SPREAD
mu	0.000507	0.000474
	(0.000333)	(0.000403)
mxreg1	-0.088432***	-0.134271***
	(0.005714)	(0.020017)
Monday Effect	0.002793***	0.001762**
	(0.000775)	(0.000985)
January Effect	0.0004	0.001835
	(0.00166)	(0.001809)
omega	0	0.000007***
	(0.000000)	(0.00000)
alpha1	0.002932	0.135522***
	(0.006290)	(0.033045)
beta1	0.990593***	0.67703***
	(0.007417)	(0.050083)
LogLikelihood	986.7973	930.98

Note. Results for JEPQ of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.9 VIX and Spread effect on JPST

	VIX	SPREAD
mu	0.000227***	0.000238***
	(0.0)	(0.000022)
ar1	-0.10055*	0.028497
	(0.064524)	0.068848
ar2	-0.047464*	-0.089641
	(0.063081)	0.064448
ar3	-0.153549***	-0.029712
	(0.066086)	0.066576
mxreg1	-0.000354	0.004643***
	(0.000382)	(0.001271)
Monday Effect	-0.000107**	-0.000106**
	(0.000058)	(0.000056)
January Effect	0.00004	-0.000001
	(0.000080)	(0.000112)
omega	0	0
	(0.000000)	(0.000001)
alpha1	0.056785***	0.058608
	(0.026471)	(0.042984)
beta1	0.905758***	0.905561***
	(0.041382)	(0.048632)
LogLikelihood	1631.765	1646.062

Note. Results for JPST of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.10 VIX and Spread effect on MINT

	VIX	SPREAD
mu	0.000261***	0.000277***
	(0.000010)	(0.000010)
ar1	0.141266	0.097282
	0.144728	0.140449
ma1	-0.586014***	-0.532737***
	0.12354	0.119015
mxreg1	0.00105***	0.00309***
	(0.000253)	(0.000696)
Monday Effect	-0.000089***	-0.000073**
	(0.000040)	(0.000041)
January Effect	0.000082**	0.000005
	(0.000042)	(0.000040)
omega	0	0
	(0.000000)	(0.00000)
alpha1	0.053799***	0.051738***
	(0.010207)	(0.006242)
beta1	0.901287***	0.900738***
	(0.02212)	(0.016921)
LogLikelihood	1726.874	1716.212

Note. Results for MINT of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.11 VIX and Spread effect on S&P500

	VIX	Spread
mu	0.000366	0.000206
	(0.000340)	(0.000443)
mxreg1	-0.103075***	-0.204769***
	(0.005793)	(0.021822)
Monday Effect	0.002341***	0.001802***
	(0.000791)	(0.001028)
January Effect	-0.000131	0.0014***
	(0.001629)	(0.002148)
omega	0	0
	(0.000000)	(0.000001)
alpha1	0.000353	0.000135
	(0.000418)	(0.000693)
beta1	0.982551***	0.998512***
	(0.002302)	(0.000665)
LogLikelihood	985.3227	921.3426

Note. Results for S&P500 of the ARIMA-GARCH with mean model specification (5) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

Table B.12 The estimated coefficients for the model (7)

Fund	VIX Effect	S&P500 (VIX)	Spread Effect	S&P500 (Spread)
DFAC	-0.001154	0.988703***	-0.025061***	0.965689***
ARKK	-0.028738	1.938485***	-0.049515	2.025669***
AVUV	-0.016756	1.041067***	-0.091228***	1.016489***
DFAT	-0.014247	1.052268***	0.013131***	1.022449***
DFUS	-0.001768	1.015317***	-0.01069***	1.011338***
DFUV	-0.004925	0.8614***	-0.062485***	0.807637***
JEPI	-0.017928***	0.419961***	0.009594	0.536045***
JEPQ	-0.010544**	0.750382***	0.016864	0.827942***
JPST	0.000792	0.009312**	0.007486***	0.015295***
MINT	0.001069***	0.003061	0.003848***	0.002646

Note. Estimated Coefficeint of the ARIMA-GARCH with model specification (7) for models employing VIX and Spread. Standard errors are in parentheses and significance levels are denoted ***p < 0.05, **p < 0.10, *p < 0.15.

APPENDIX C

C.1 Analysis Results

Table C.1 ADF Test for DFAC

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -14.67    0.01
[2,]   1 -11.76    0.01
[3,]   2  -9.42    0.01
[4,]   3  -7.84    0.01
[5,]   4  -6.90    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -14.79    0.01
[2,]   1 -11.92    0.01
[3,]   2  -9.60    0.01
[4,]   3  -8.04    0.01
[5,]   4  -7.13    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -14.76    0.01
[2,]   1 -11.91    0.01
[3,]   2  -9.59    0.01
[4,]   3  -8.03    0.01
[5,]   4  -7.12    0.01
```

Table C.2 ADF Test for ARKK

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -14.94    0.01
[2,]   1 -10.88    0.01
[3,]   2  -8.88    0.01
[4,]   3  -7.83    0.01
[5,]   4  -7.15    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -14.93    0.01
[2,]   1 -10.87    0.01
[3,]   2  -8.88    0.01
[4,]   3  -7.83    0.01
[5,]   4  -7.16    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -14.90    0.01
[2,]   1 -10.86    0.01
[3,]   2  -8.86    0.01
[4,]   3  -7.82    0.01
[5,]   4  -7.16    0.01
```

Table C.3 ADF Test for AVUV

```
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -15.63    0.01
[2,]   1 -12.51    0.01
[3,]   2  -9.48    0.01
[4,]   3  -8.22    0.01
[5,]   4  -7.82    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -15.66    0.01
[2,]   1 -12.56    0.01
[3,]   2  -9.54    0.01
[4,]   3  -8.29    0.01
[5,]   4  -7.92    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -15.63    0.01
[2,]   1 -12.53    0.01
[3,]   2  -9.52    0.01
[4,]   3  -8.27    0.01
[5,]   4  -7.90    0.01
```

Table C.4 ADF Test for DFAT

```
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -15.88    0.01
[2,]   1 -12.41    0.01
[3,]   2  -9.48    0.01
[4,]   3  -8.17    0.01
[5,]   4  -7.66    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -15.89    0.01
[2,]   1 -12.45    0.01
[3,]   2  -9.52    0.01
[4,]   3  -8.22    0.01
[5,]   4  -7.73    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -15.86    0.01
[2,]   1 -12.42    0.01
[3,]   2  -9.50    0.01
[4,]   3  -8.20    0.01
[5,]   4  -7.71    0.01
```

Table C.5 ADF Test for DFUS

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -14.74    0.01
[2,]   1 -11.59    0.01
[3,]   2  -9.45    0.01
[4,]   3  -7.57    0.01
[5,]   4  -6.71    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -14.91    0.01
[2,]   1 -11.81    0.01
[3,]   2  -9.71    0.01
[4,]   3  -7.84    0.01
[5,]   4  -7.01    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -14.88    0.01
[2,]   1 -11.79    0.01
[3,]   2  -9.70    0.01
[4,]   3  -7.83    0.01
[5,]   4  -6.99    0.01
```

Table C.6 ADF Test for DFUV

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -14.62    0.01
[2,]   1 -11.46    0.01
[3,]   2  -9.09    0.01
[4,]   3  -7.95    0.01
[5,]   4  -7.27    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -14.68    0.01
[2,]   1 -11.54    0.01
[3,]   2  -9.18    0.01
[4,]   3  -8.07    0.01
[5,]   4  -7.42    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -14.68    0.01
[2,]   1 -11.56    0.01
[3,]   2  -9.21    0.01
[4,]   3  -8.10    0.01
[5,]   4  -7.44    0.01
```

Table C.7 ADF Test for JEPI

```
 Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -14.48    0.01
[2,]   1 -11.00    0.01
[3,]   2  -9.69    0.01
[4,]   3  -7.95    0.01
[5,]   4  -6.65    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -14.55    0.01
[2,]   1 -11.10    0.01
[3,]   2  -9.83    0.01
[4,]   3  -8.10    0.01
[5,]   4  -6.80    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -14.53    0.01
[2,]   1 -11.08    0.01
[3,]   2  -9.82    0.01
[4,]   3  -8.09    0.01
[5,]   4  -6.79    0.01
```

Table C.8 ADF Test for JEPQ

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
[1,]   0 -15.19    0.01
[2,]   1 -11.06    0.01
[3,]   2  -9.48    0.01
[4,]   3  -7.48    0.01
[5,]   4  -6.51    0.01
Type 2: with drift no trend
     lag    ADF p.value
[1,]   0 -15.53    0.01
[2,]   1 -11.45    0.01
[3,]   2  -9.96    0.01
[4,]   3  -7.95    0.01
[5,]   4  -7.02    0.01
Type 3: with drift and trend
     lag    ADF p.value
[1,]   0 -15.50    0.01
[2,]   1 -11.43    0.01
[3,]   2  -9.93    0.01
[4,]   3  -7.93    0.01
[5,]   4  -7.01    0.01
```

Table C.9 ADF Test for JPST

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
  [1,]   0 -12.03    0.01
  [2,]   1  -8.60    0.01
  [3,]   2  -6.91    0.01
  [4,]   3  -4.96    0.01
  [5,]   4  -3.84    0.01
 Type 2: with drift no trend
     lag    ADF p.value
  [1,]   0 -15.40    0.01
  [2,]   1 -12.33    0.01
  [3,]   2 -11.28    0.01
  [4,]   3  -8.89    0.01
  [5,]   4  -7.29    0.01
Type 3: with drift and trend
     lag    ADF p.value
  [1,]   0 -15.49    0.01
  [2,]   1 -12.45    0.01
  [3,]   2 -11.43    0.01
  [4,]   3  -9.04    0.01
  [5,]   4  -7.46    0.01
```

Table C.10 ADF Test for MINT

```
Augmented Dickey-Fuller Test
  alternative: stationary

 Type 1: no drift no trend
     lag    ADF p.value
  [1,]   0 -10.64  0.0100
  [2,]   1  -5.27  0.0100
  [3,]   2  -3.34  0.0100
  [4,]   3  -2.46  0.0154
  [5,]   4  -1.80  0.0721
 Type 2: with drift no trend
     lag    ADF p.value
  [1,]   0 -22.24    0.01
  [2,]   1 -14.58    0.01
  [3,]   2 -11.39    0.01
  [4,]   3 -10.12    0.01
  [5,]   4  -8.55    0.01
Type 3: with drift and trend
     lag    ADF p.value
  [1,]   0 -22.20    0.01
  [2,]   1 -14.56    0.01
  [3,]   2 -11.38    0.01
  [4,]   3 -10.13    0.01
  [5,]   4  -8.58    0.01
```

Table C.11 Sign Bias Test and ARCH-LM Test Results

	Sing Bias (p-value)	ARCH-LM (p-value)
DFAC (VIX)	0.6721	0.7081
DFAC (SPREAD)	0.3839	0.3323
ARKK (VIX)	0.5208	0.2514
ARKK (SPREAD)	0.8528	0.3513
AVUV (VIX)	0.7387	0.848
AVUV (SPREAD)	0.697	0.7732
DFAT (VIX)	0.7513	0.7481
DFAT (SPREAD)	0.7201	0.5635
DFUS (VIX)	0.6927	0.2779
DFUS (SPREAD)	0.1661	0.8331
DFUV (VIX)	0.3771	0.9463
DFUV (SPREAD)	0.7898	0.1903
JEPI (VIX)	0.57351	0.3385
JEPI (SPREAD)	0.9965	0.5497
JEPQ (VIX)	0.0724033	0.02206
JEPQ (SPREAD)	0.8979	0.4358
JPST (VIX)	0.07609	0.9908
JPST (SPREAD)	0.4028	0.9747
MINT (VIX)	0.061668	0.3779
MINT (SPREAD)	0.039251	0.8735